Essays on Learning Outcomes and Education in México

Vicente Antonio García Moreno

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ABSTRACT

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The objective of this dissertation is to present empirical evidence and analysis of three key issues in the Mexican education system: 1) school accountability, as reflected in a particular state innovation pursued by the state of Colima in 2009 to identify and address the problems of low-performing schools, 2) age delay and the effects of a national reform introduced in 2006-2007 that modified the first grade entry-age across all Mexican states, and 3) the educational disadvantages of indigenous peoples in México and their consequences, as determined from recent data which allows identification of this population.

First, the dissertation evaluates the impact of a targeted state-sponsored intervention program known as Programa de Atención Específica para la Mejora del Logro Educativo (PAE) designed to provide low-performing schools with remedial resources in Colima, México. The research analyzes the effect of this compensatory program in terms of standardized test scores among 108 participating schools having the lowest learning outcomes in 2009. The results of this "natural experiment" confirm that intervention in the form of the PAE program had a positive impact on average test scores in poorly performing Colima schools. By exploiting PAE's eligibility rules, a regression discontinuity method is used to estimate the impact on subsequent learning outcomes. Schools that participated in the program and a valid comparison group were followed for three years in order to compare their performance. The fact that the program was halted after only one year meant that the only realized interventions were those related to the program's preparation, which revolved around notifying schools as low-performing, identifying a school's main academic problems and devising a development plan to address those challenges. Yet, after only one year, test scores in PAE schools increased by 0.13 standard deviations vis-à-vis non-PAE schools and in fact, after three years, differences between the two groups of schools were no longer significant.

Second, the dissertation explores the impact of exogenous variation in the age at which students enter school on education outcomes. Prior to the 2006-2007 school year, the cut-off day for school entry in Mexico had been September 1st. Since then, however, pupils aged 6 by as late as December 31 could start public school. Data related to this cut-off transition are reviewed and analyzed using a regression discontinuity method so as to estimate the causal effect of delayed school enrollment on math test scores. A two-stage least square (TSLS) estimator is used wherein the source of identification is the variation in 1st grade entry ages which resulted solely from differences in dates of birth. The results indicate that older students scored higher than younger students. The reform impacted the discrepancy between those regulated by the new cut-off dates and those regulated by the old cut-off date(s) by 0.30 s.d. (comparing the 1998-1999 cohort which entered school before the reform with the 2002-2003 cohort, which entered afterwards). The results also suggest age effects on education outcomes that are stronger for recent generations than for generations entering first grade prior to the reform. Because math scores have increased by 0.95 s.d. since the first administration of ENLACE in 2006, this result suggests that, at a minimum, moving the cut-off date by four months to December 31 did not have an adverse effect on mean math test scores.

Finally, a sobering analysis of the educational outcomes of indigenous populations is conducted using data from Encuesta Nacional Ingresos y Gastos de los Hogares, ENIGH) which, for the first time in 2008 and then 2010 identified indigenous populations. The research finds that although the percentage of families in extreme poverty residing in municipalities where indigenous populations are concentrated dropped between 1992 and 2010, the gap in poverty rates between the municipalities where indigenous people concentrate and others remains huge, with extreme poverty in the former equal to 51.9% in 2010 and in the latter 16.9%. Because rates of return to education are estimated in this dissertation to be high in Mexico (around 10%, including those for indigenous populations), education is found to be essential in reducing the gulf in poverty levels by ethnicity.

But the study shows that gaps in educational outcomes between indigenous and non-indigenous populations remain wide, whether in terms of average educational attainment, participation in Kindergarten, the percentage of students who are overage, and the average student achievement as measured by a variety of tests.

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Nomenclature

ANMEB	National Agreement for the Modernization of Basic Education
CEC	Concurso de Escuelas de Calidad
CES	Colima Education System
CNTE	Coordinadora Nacional de Trabajadores de la Educacion
CONEVA	Consejo Nacional de Evaluacion de la Politica de Desarollo Social
ECD	Early childhood development
EPF	Education Production Function
ENIGH	Encuesta Nacional de Ingreso y Gasto de los Hogares
ENLACE	National Evaluation of Academic Achievement in School Centers
INEE	Instituto Nacional de Evaluacion Educativa
INEGI	Instituto Nacional de Geografia
MES	The Mexican education system
PAE	Programa de Atencion Especifica para la Mejora del Logro Educativo
PEC	Programa de Escuelas de Calidad
PECD	Programa de Estimulo a la Calidad Docente
PEMLE	Programa Emergente para la Mejora de Logro Educativo
PISA	Program for International Student Assessment
OECD	Organization for Economic Co-operation and Development
SBM	School Based Managment
SEP	Secretaria de Educacion Publica

SINAIS	Sistema Nacional de Informacion en Salud
SNTE	Sindicato Nacional de Trabajadores de la Educacion
TIMSS	Third International Mathematics and Science Study
TSLS	Two Stage Least Square
UNICEF	United Nations Children's Fund
WB	The World Bank
911	School Census data

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To my parents, my sisters, my niece and my nephew.

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Chapter 1

Introduction

México faces many challenges in its efforts to improve the wellbeing of its people, in particular, those who are socially and economically disadvantaged. This is México's "Perennial Challenge." According to the World Bank, México is a middle-income country, and the world's 11th largest economy, yet México's economic performance is poor in terms of economic growth, with an average growth rate of only 0.6% from 1993 to 2013 (INEGI, 2014a). In 1992, 53% of México's population experienced moderate poverty, and after the 1994 economic crisis, poverty rose until late 1990s, decreased until 2006 but then rose again. By 2012, 53% of México's population was again classified as living in moderated poverty (CONEVAL, 2014). Despite twenty years of public policy efforts in social and educational programs, México has failed to reduce its poverty rate. México faces great—seemingly insurmountable—challenges of economic development [1].

To be sure, the Mexican people have achieved some great advancements in education. Figure 2.3 in Annex depicts gross enrollment in México, where enrollment increased after the Mexican revolution, and greatly expanded in the last 60 years. But these successes have not been matched by substantial increases in education achievement as measured by international achievement tests.

[1] see Figure 2.8 in the annex for more details on the evolution of poverty in México from 1992 to 2012

México's participation in the Program for International Student Assessment (PISA) sponsored by Organization for Economic Co-operation and Development (OECD) reflects comparatively poor academic achievement. PISA provides a measure of reading, mathematics and science achievement designed for international comparisons. PISA's international assessment focuses on young people's ability to apply their knowledge and skills to real-life problems and situations, rather than on how much curriculum-based knowledge they may possess. Students from México are among the worst performers. In PISA 2003, México scored 385 points in math and by 2012 had scored 413 points, an increase of only 28 points over almost a decade. In 2000, México achieved a greater total of 422 points in reading, but by 2012 had increased its average reading by a mere two points. With respect to science, México actually lost ground, decreasing from 422 to 415—a loss of 7 points in this period. By comparison, México's most important economic partner, the USA, achieved 68 points higher in math than México in PISA 2012. México is far from close the gap with developed countries in this achievement test.

So while educational enrollments have increased, student achievement has not kept pace. This relationship between enrollment and achievement, however, may not be merely coincidental: It is possible, as some researchers have claimed, that poor achievement results are associated with increasing enrollment. With more and more children entering and completing basic education than ever before, new entrants are more likely to come from marginalized households where malnutrition and poverty are more prominent, and illiteracy is more widespread (World-Bank, 2006).The process of learning for these economically disadvantaged children is more challenging and this may be reflected in comparatively lower student achievement in schools, as measured say by test scores. In addition, the educational system may not have been adequately prepared –in terms of resources, quality of public sector management, etc.—to handle the increased enrollments. Because of this, México may have been subject to a painfully ironic educational dynamic: the more who are taught, the less is learned.

Given this state of affairs, a number of educational reform movements have been undertaken or proposed. Some have emphasized the inequalities across regions, states and ethnicity (Sáenz, 1939; Prawda, 1989; World-Bank, 2006; Mexicanos-Primero, 2013). Some education authorities want to address the low quality of education through the implementation of educational policies and structural reform policies targeting the cognitive achievement of Mexican students. To this end, a number of policymakers, education authorities, and researchers have suggested that decentralization as a key factor to improve México's education system. According to Merino-Juárez (1999) , "proponents of decentralization point to the potential for experimentation and innovation in educational programs." Others support centralization of the education system while still others support some sort of school "autonomy": adjusting and contextualizing educational programs to deliver better services. And still others stress the importance of transparency and accountability of school actors and educational authorities, pointing, for example, at accountability policies designed to increase school quality like teacher incentive programs.

Reforms come from other directions too. Teachers unions push for increases in salaries as well as resources while families and the private sector pursue their own interests and agendas. At the end, there is a national recognition of the problem, but there is no consensus on how to improve the quality of education nor a consistent educational agenda in the Mexican society. Worse, different and competing perspectives can wear down even the best good faith efforts among reformers.

The objective of this doctoral dissertation is an analysis of three different issues relating to learning outcomes in México: 1) the impact of a specific educational policy targeting low-performing schools in Colima, México, called Programa de Atención Específica para la Mejora del Logro Educativo (PAE), or Program of Focused Attention fro the Improvement of Educational Outcomes and 2) the effects of entry-age as a structural factor impacting learning, and 3) the various dimensions of the educational disadvantages of indigenous people in México. Each issue is addressed separately in Chapters 3, 4 and 5. An introductory Chapter 2 provides an overview of the Mexican education system, detailing the structure of the education system, access, demand, principal reforms, expenditure, evaluation system and learning outcomes.

Chapter 3 evaluates the impact of the educational intervention called Programa de Atención Específica para la Mejora del Logro Educativo (PAE), which identifies and targets low-performing schools and provides resources to improve them. The research analyzes the effects of this compensatory program on improving the education quality of schools in Colima, México. The PAE program targets 108 schools that in 2009 obtained the lowest learning outcomes measured by the country's student assessment.

Chapter 4 explores the exogenous variation in education related to dates of birth. That is, some individuals inevitably start school one year later than their cohorts merely due to an entry-age cut-off. For instance, in the school year spanning 2006-2007, the entry-age cut-off day had been September 1. Since then, however, pupils aged 6 by December 31 could start public school. Data related to this cut-off transition are reviewed and analyzed, and a regression discontinuity method is used to estimate the causal effect of delayed school enrollment on student outcomes in México. A two-stage least square (TSLS) estimator is used in which the source of identification is the variation in the 1st-grade entry age that results solely from differences in date of birth. Nevertheless, sensitive statistical checks are performed to understand if other possible mechanisms may explain any learning improvements. This section includes sub-sections which review the current literature on age effects, describe a theoretical model analyzing age effects, provide the data and context of entry-age reform and discuss methodology and results.

Chapter 5 identifies and describes the dimensions of educational inequality facing the indigenous populations of México. In particular, the analysis explores unequal learning environments, poor schooling outcomes, lack of transitions to higher education and low returns on educational investments. A final chapter 6 offers some conclusions and discusses some policy implications.

Chapter 2

Education in México

This chapter provides a targeted survey of educational indicators and the education system in México. First, it analyzes the demand side and the demographics behind it. In addition, it describes the basics of the Mexican education system and its principal reforms. It discusses expenditures in education as well as the information and evaluation systems adopted. Finally, it describes the state of learning in México.

2.1 The rising demand for education in México

México is a country with an estimated population of about 120 million, with 55% of the population below the age of 30 years. The median age of the Mexican population is 26 years old. México is therefore a young country (INEGI, 2014b). This is reflected in rising enrollment of children in schools. In the school year 2012-2013, the demand for compulsory education amounted to 35 million young Mexican students in ages from 3 to 18 years (preschool to 12th grade). This is a historic high in terms of enrollment.

Nevertheless, in 2013, the fertility rate was only 2.2 children per woman and has decreased over the last 20 years by 1.4 children per woman (CONAPO, 2013). So while México is currently experiencing the highest demand for compulsory education in its history decreasing fertility rates suggest that 35 million may well be a demand peak. Extrapolating from the fertility rates and number of births from 1992 to 2012 issued by the National Heath Information System (Sistema Nacional de Información en Salud- SINAIS), by 2020 the Mexican education system will need to accommodate only 31 million students aged 3 to 18. Given that demand pressures are relaxing, the current decade is a moment of historic action to improve education in México. But the demand for education in México is not just related to the demographics. Despite slow growth, the country has achieved higher per-capita income over time and, as will be detailed later, rising enrollment rates have led to significant increases in educational attainment over time. But as parents become more educated, the demand for their children's education also rises.

Figure 2.1 shows the average years of schooling of both mother and father by year of birth of their children. A mother's education for those born in 1985 was, on average, about 5.5 years of schooling and a father's education was about 6.4 years. Though males are more educated than females, this gap has been reduced by about 0.15 years of schooling for those born since 2008. For the most recent generation (those born in 2008), the average years of schooling for either parent is over 8.5 years. With better educated adults and parents, the demand for better educated children increases.

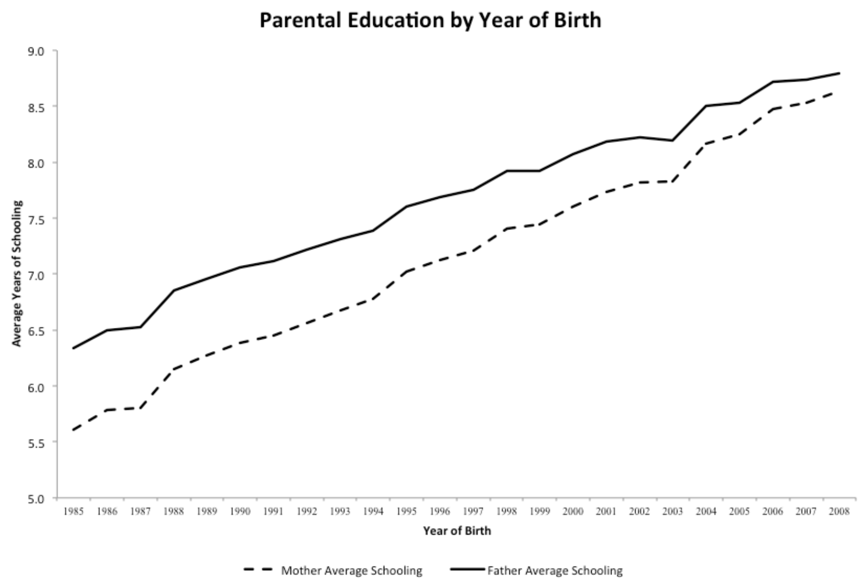

Figure 2.1: Average parental education by year of birth. Source: SINAIS

How has the increased demand for schooling translated into supply? The next section examines the transformation of the Mexican school system over time.

2.2 Mexican education system and its principal reforms in the last 20 years

From a normative point of view, an education system is a group of rules, laws and norms defined by the social contract of a society. In México, the social contract governing education has been principally codified in the form of the Mexican Constitution; in particular Articles 3 and 31. The second most important law is the Education Law which defines the organization, administration and role of government, society, parents and private sector with respect to Mexican education. The Mexican education system (hereafter MES) is organized into five levels: preschool (P1-P3), primary school (grades 1-6), lower secondary education (grades 7-9), upper secondary education (10-12) and higher education. By right of law, schooling in México is compulsory from preschool to grade 12 (see Annex, Table 2.6 for details on the organization of the MES). The government dominates the supply of schooling.

In the school year 2011-2012, only 13% of the total provision of education (in terms of student population) was offered for by the private sector (SEP, 2013). However, the amount of private expenditure increases with respect to the level of education being funded (with the exception of preschool): for basic education, 9%, 8% for grades 1 to 9, and 14% for preschool. In grades 10 to 12, the private sector covered 17.4% and a full 32% of higher education.

The MES is a complex nation-wide system responsible for many levels of education across widely disparate populations. For that reason, the following description of the MES is focused on preschool and grades 1 through 6. The Ministry of Education (Secretaria de Educación, SEP) is responsible of the organization, regulations and the governance of the MES. Along with SEP, state education authorities and the teachers union (Sindicato Nacional de Trabajadores de la Educacion -SNTE), are the three main actors within the MES.

The starting point of the modern Mexican education system is the Mexican Revolution (1910-1920)—a social movement which, among other notable developments, recognized the unequal conditions and opportunities of Mexicans. In particular, the revolution highlighted the plight of some of México's most disadvantaged: its indigenous people. According to Sáenz (1939), the Mexican Revolution was not from the indigenous population. Rather, it was for the indigenous. At the same time, "Mexicanization" part of the revolution offered both land and books. In the ten years after the revolution, public school enrollment increased from 12,000 to 22,000, mostly through advances in rural schools—one of the promises of the revolution. After this initial period, the history of the MES can be demarcated into four periods: 1) institutional consolidation, 2) bureaucratic and corporative autocracy followed by economic crisis, 3) decentralization and 4) the present system.

The consolidation of the MES was possible through investment in education by post-revolutionary governments, specifically through a long term plan called the "Eleven Years Plan" from 1958 to 1970. During this plan, educational inequalities due to greater urbanization and rising state disparities in income per-capita increased but advances in basic access were nevertheless widespread (Prawda, 1989).

During the late 1970s, México focused on developing its oil resources and it benefited from elevated oil prices, but economic mismanagement and increasing international debt let to a debt crisis in 1982 that affected public finances throughout the 1980s. For example, the salary of a primary teacher with a university degree decreased by 36.1% between 1983 and 1988 (Prawda, 1989). Even while advances were made in access to preschool and grades 1 to 9, public and private spending fell in throughout the 1980s. According to Prawda (1989) inequality among states in terms of access, spending, organization and quality persisted. Merino-Juárez (1999) states "as the centralization process was not equally strong everywhere, the large differences between the states regarding the amount of resources spent per student or per capita became determined by the relative size of the state system"(p. 69). At that time, Prawda (1989) claimed that inequalities could be resolved by structural changes in the education system realized through decentralization, reorganized priorities and more funding.

Prior to 1994, México had a centralized education system, with all relevant decision-making taking place at the national level. In 1992, the Mexican federal government, the states and the teachers union agreed to a process of decentralizing the education system. This reform gave the states the responsibility for providing basic education (grades 1 through 9), professional development for teachers and infrastructure for schools (Merino-Juárez, 1999). However, the federal education authority remained responsible for pedagogical content, education policies, information and evaluation systems and disadvantaged populations in isolated rural areas. (Compensatory programs for disadvantage populations have been in operation since the early 1990s.). In addition, the reforms associated with decentralization made 7th to 9th grade compulsory and included a pay scheme program for teachers known as the Teacher Carrier Program (Carrera Magisterial).

Many researchers argue that the education system remained highly centralized even under this "administrative decentralization" (Alvarez et al., 2007). The Ministry of Education retained some centralized power arguing that education must have nation-wide minimum standards, similar curricula and qualification requirements. Furthermore, Merino-Juárez (1999) claims that "the decentralization did not change key aspects of education policy or the incentives beyond education that affect funding decisions across all public services provided by the state" (p. 123).

2.2.1 The current Mexican education system and Recent reforms

In 2000, México transitioned from a party which had ruled for 70 years (Partido Revolucionario Institucional, PRI) to an opposition party with right-leaning ideology, Partido Accion Nacional (PAN). A number of significant educational reforms were implemented during the first six years of the new government. Among these reforms was the creation of the National Institute for Evaluation of Education (INEE), intended to ensure education accountability (Mexicanos-Primero, 2007). Prior to the creation of INEE, educational authorities, principals and teachers were not accountable. For example, in 1995, México participated in the Third International Mathematics and Science Study (TIMSS-1995), and performed very poorly. In fact, the results never were published and most of the Mexican TIMSS-1995 data were destroyed (Solano-Flores et al., 2005). INEE was founded in August 2002 with the aim of providing adequate, rigorous and more transparent evaluations of the basic and secondary education system. A main objective of INEE is to consolidate the national evaluation system with the objective of increasing the quality of Mexican education.

Other objectives include: (1) coordinating international evaluations, (such as PISA); (2) developing an indicator system based on the information collected by SEP; and (3) developing models for the evaluation of schools as an organizational unit (Mexicanos-Primero, 2007). In September of 2013, an educational reform was approved by the Mexican congress which gave it the power to control the evaluation system in México.

In 2002, the Mexican congress approved preschool reforms which included a modification of the curriculum, credentials for educators (at the preschool level) and three years of compulsory kindergarten (from age 3 to 5). The main objective of these reforms were to reduce disparities across gender, race and economic status so that pupils would enter primary school on a more equal basis. The implementation of three compulsory years of kindergarten was phased in: The third year of kindergarten became obligatory in the school year 2004-2005, the second year in 2005-2006 and the first year in 2006-2007. Intended to guarantee universal preschool education, data from UNICEF indicated that 98% of five year olds were enrolled in preschool by 2005. Moreover, enrollment in first and second year preschool also increased, but with less intensity (UNICEF, 2007). Figure 2.2 shows the enrollment in the 2nd and 3rd grade of preschool since the reform was approved. Enrollment for both grades increased in the school year 2003-2004, then reached its highest in enrollment in the school year 2006-2007 for 2nd grade and in the following school year for 3rd grade. After that peak, enrollment remained stable for both grades.

Moreover, the law stipulated that only third year of kindergarten is a requirement to enter to 1st grade but it was not enforced until the school year 2006-2007 due to the school entry age reform that was also undertaken. That is, it was enforced in 2006 as a requisite to enter to 1st grade due to the school age cut-off reform (more details on these two reforms in chapter 4).

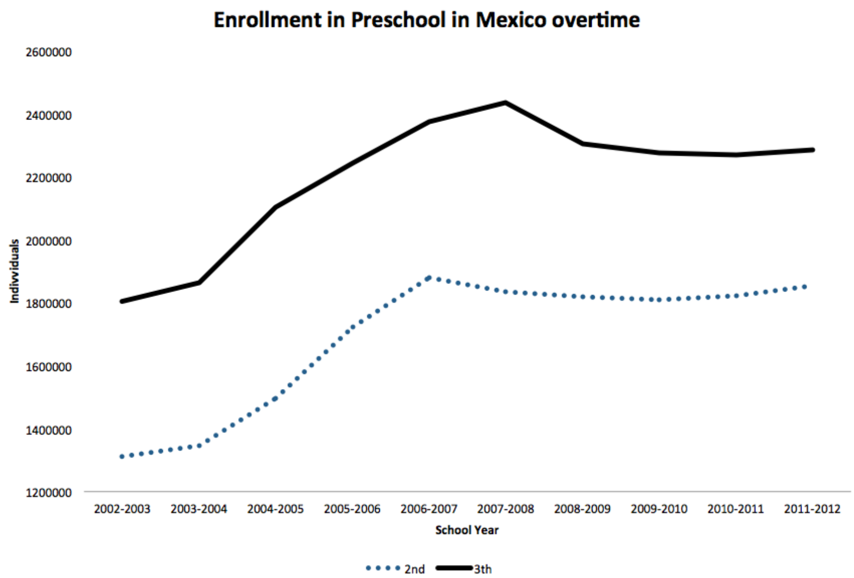

Figure 2.2: Preschool Enrollment in México. Source: SEP

In 2002, the Vicente Fox administration created the Quality Schools Program (Programa de Escuelas de Calidad -PEC) to improve the administration of schools as well as the dialogue between principals, teachers and parents in the most marginalized schools in México. PEC provides monetary resources to schools to implement school plans designed by parents, teachers and principals. In addition, the government launched a reform of secondary education, completed in 2009. This reform had a significant component based on teacher professionalism.

As a part of an accountability program in 2010, the Ministry of Education launched a teachers incentive program using the National Evaluation of Academic Achievement in School Centers (ENLACE) to increase school quality. The Programa de Estímulo a la Calidad Docente (PECD), a monetary incentive program, was designed to reward teachers in high-performing schools. These programs are defined as bonus or "merit pay" schemes that provide a financial reward to teachers for their performance (Bruns et al., 2011). The reasoning is that, since student learning depends on teacher performance, teachers will increase their effectiveness and productivity through direct monetary incentives. However, an quasi-experimental evaluation by Franco (2013) shows that the program did not have any impact on learning measured by ENLACE test.

In 2013, México continued reform efforts, including tackling corruption in the sector. For instance, early 2013, Elba Esther Gordillo, head of México's Teachers' Union, was jailed on accusations of corruption. President Enrique Peña Nieto also signed a constitutional amendment introducing a number of key education reforms. Most of the reforms addressed professional career issues and teacher termination. In addition, the INEE was given more power to administer the system of teacher and student evaluations. Also, the reform introduces a new information system incorporating a national school census with rosters of student, teachers and principals.

2.2.2 Expenditure in Education in México

In 2010, the spending per student in México was below the mean level for OECD countries. For example, the average spending of preschool per student was \$6,762 in OECD countries while in México it was only \$2,288. On the other hand, part of the reason for the lower spending per student in México relative to the OECD average is its comparatively lower income per-capita. Indeed, if one calculates the overall total expenditure in education as a percentage of Gross Domestic Product (GDP), it was about 6.2%, which is about the average for the OECD. In addition, the figure for 2010 represents a 1% increase over the 5 rate in 2000 (OECD, 2013).

Most of this expenditure is public. In 2010, 82% of total expenditures on education in México were a result of government expenditures. But these expenditures are not equally distributed across the country. Spending per student in México is subject to great variation due to unequal distributions among levels, states and populations. For example, the average spending per student in basic education is \$1,670 per school year, but across Mexican states this figure changes and is lower in states with disadvantaged populations (e.g., Chiapas's unit cost is \$1,117). According to Mexicanos Primero (2013), the uneven distribution of education resources in México reinforces social inequalities especially among disadvantaged populations.

This is not a recent phenomenon. Expenditures on education at the state level have differed significantly from year to year and from place to place. According to Merino-Juárez (1999), between 1985 to 1991, Baja California spent 32 times more than Oaxaca, and "the highest spenders are the northern states which also tend to be wealthier and more industrialized (Baja California, Chihuahua, Coahuila, Nuevo Leon, Sinaloa, Sonora and Tamaulipas)" (p. 52). Federal spending on education does not necessarily help in reducing spending inequities across states. In 2013, the actual administrative financing for education in México relied heavily on federal transfers or direct transfers of monetary resources to education institutions (in the case of higher education) at a rate of 62% of total expenditures (both public and private). According to Merino-Juárez (1999), "Federal transfers for education to the states are not allocated according to the equalizing criteria stated by the decentralization agreement and the new education legislation" (p. 122). Just after decentralization, states increased their expenditure in education as well as the transfers from the government (Merino-Juárez, 1999).

In México, private household expenditures on education also vary by income distribution, region and ethnicity. According to INEGI (2013), the percent of household expenditure on education has actually decreased by -1.7% from 2006 to 2012. In 2006, the percent expenditure on education as a percentage of total household expenditure was 15.5%, while in 2013 this percent was 13.8%. By contrast, in the richest percentile of the income distribution, the percent of expenditure reached almost 20%. Predictably, the bottom 10% of the income distribution spent only 5.2% of their total income on education (INEGI, 2013). Moreover, the expenditure gap in education between rural and urban areas was 6.1% in 2012.

2.2.3 Information and Evaluation System

Since the decentralization of education in 1993, there have been a variety of educational interventions by SEP, the states as well as the private. How has student achievement changed over time? In order to measure comparative student achievement, México participated in an international assessment (Trends in International Mathematics and Science Study, TIMSS) for the first time in the middle of the 1990s. However, due to very low performance, the results never were published. The starting point of an evaluation system began in 1998 with the application of the first standardized test-sample format designed by the Department of General Evaluation in Education as part of the SEP. This process was institutionalized with México's participation in PISA 2000 and the creation of the INEE. Since decentralization, several states have developed their own information and evaluation systems, like Colima which, since 1997, has applied a local test and published its own results. However, since 2006, the Ministry of Public Education has administered the National Evaluation of Academic Achievement in School Centers (ENLACE) nationwide. The ENLACE evaluates students at the primary, secondary and upper secondary school levels.

ENLACE deploys and coordinates the activities of 133,000 persons to supervise the application of assessments: teachers are not allowed to administer exams to their own students and parents are not allowed to supervise their own children. The SEP's Department of Policy Evaluation (the agency in charge of ENLACE before the reform created the National Evaluation Institute in 2013) used the K-index and Scrutiny methods to detect cheating on suspicious answer strings. Student scores are calculated on the basis of items answered correctly weighted by the difficulty of the item on a scale ranging from 200 to 800, with a mean of 500 and standard deviation of 100. (For comparisons over time, 2006 is used as the base year.) Because ENLACE is administered annually during the National Week for Evaluation (in April to early June), everyone—students, parents, teachers, principals, etc.—know exactly when the exam will be applied through an initial school year document distributed before the start of the school year.

2.3 State of Learning in México

With more and more children entering and completing basic education than ever before, it is often claimed that expanding access inevitably leads to decreasing the quality of education. New entrants are more likely to come from marginalized households where malnutrition, poverty and illiteracy are more common.This makes the schooling of these children a great challenge for the school system. In addition, in the absence of additional resources and support, expanding school and classroom enrollments constitute a great challenge for schools and teachers, which can have a negative impact on learning.

For this reason, national assessments can provide insights into which students are progressing and meeting curriculum goals, which teachers are most effective and also signal which policies and strategies are having the desired effect.

Figure 2.3 depicts gross student enrollment in México, where enrollment in the first six grades had increased after the Mexican Revolution and has expanded in the last 60 years. Enrollment for other levels of education, however, does not follow the same trajectory. According to Prawda (1989), for every 100 students who started 1st grade in 1982, only 53 completed 6th grade. But these figures are based upon aggregated averages across states. For example, in México City, 86 of 100 finished 6th grade. By contrast only 55 of 100 in Colima finished 6th grade. The worst 6th grade completion rates, though, occurred in those states with greater indigenous populations: Tabasco (48 students), Campeche (45 students), Veracruz (43 students), Michoacán (42 students), Yucatan (41 students), Guerrero (40 students). Oaxaca (40 students) and Chiapas (29 students).

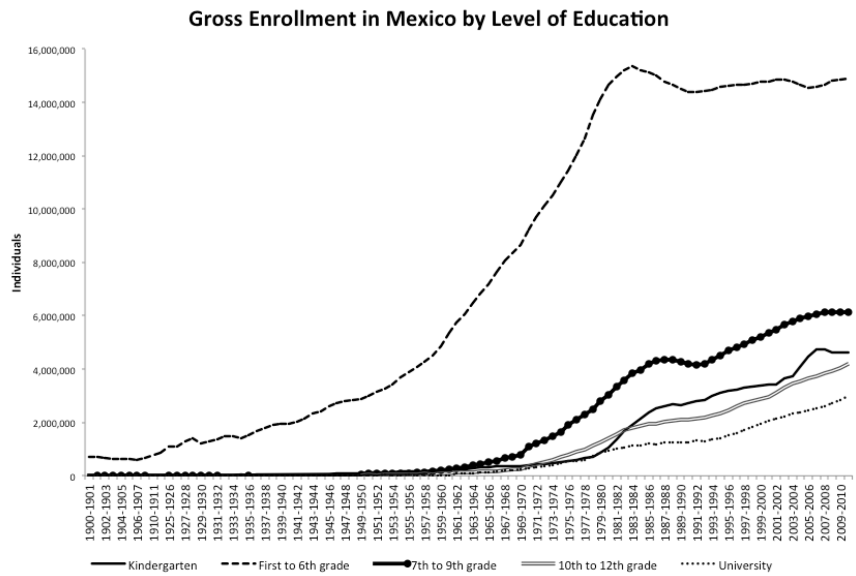

Figure 2.3: Gross Enrollment in México by Level of Education. Source: SEP

So while 6th grade completion rates clearly vary from state to state, enrollment rates also vary through time. Using the Mexican Expenditure and Income Household Survey, Table 2.1 shows the percentage of children attending school by generational cohort. While 17% of the 1992 generation was not attending school at age six, their attendance nevertheless increased to 98% by age 8. However, this generation started leaving school at a greater rate by the age of 14 and 16, with 16% and then 38% attrition rates respectively. Generally, the greatest percentage of children was in school at the age of 6. In 2012, for example, a full 98% of 6-year-olds were attending school, and by age 12, most of these students were still attending school, presumably in the 7th grade. Yet many of these students drop out at the secondary school level. By the 10th grade, more than 30% were no longer attending school.

Figure 2.4 shows the population not in school at the ages of 5 and 6. During the 1990s, the MES was very efficient in increasing enrollment as reforms in preschool education were implemented. In 1992, 5-year-olds were not obligated to attend school (though they were encouraged). In fact, in 1992, 37% of 5 year olds was not attending any type of education. In 2000, this number was 13%. By 2002, however, preschool was compulsory (more details in the reform subsection) and

Table 2.1: Six Years Old Generation and their percentage not attending school

Generation	6	8	10	12	14	16
6-1992	0.17	0.02	0.04	0.07	0.16	0.38
6-1994	0.08	0.02	0.03	0.06	0.17	0.37
6-1996	0.05	0.04	0.03	0.05	0.15	0.38
6-1998	0.07	0.02	0.02	0.03	0.13	0.38
6-2000	0.06	0.01	0.01	0.03	0.13	0.34
6-2002	0.05	0.01	0.01	0.04	0.13	0.31
6-2004	0.02	0.02	0.01	0.05	0.14	
6-2006	0.04	0.02	0.02	0.04		

Source:Author's calculation using ENIGH 1992,1994, 1996,1998,2000, 2002, 2004,2006, 2008,2010, and 2012

only 6% of children aged 5 were not in school—an 8% reduction from the previous year. In 2012, only 2% of children of this age were not attending any type of schooling.

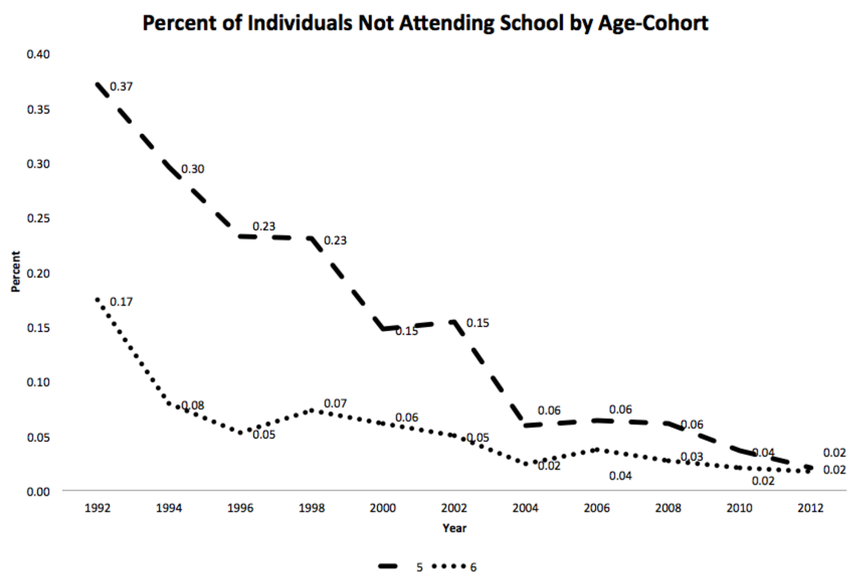

Figure 2.4: Percent of Individuals Not Attending School by Age-Cohort. Source:Author's calculation using ENIGH

A similar story emerged with children aged six. In 1992, 17% of this generation were not in school, but this figure decreased throughout the 1990s. By 2012, this number was only 2%.

Table 2.5 in the annex shows the percent of population not attending school by age. In 1992, 11% of the population aged 12—those transitioning between grade 6 and 7 (between primary and secondary schooling)—had dropped out. Moreover, ages older than 12 attend at even lower rates (though these attrition rates have reduced since 1992). For example, 47% of 16-year-olds were not in school in 1992. This number was 10% less in 2000 and 16% less in 2012—significant progress—but over 30% still remain out of school.

The Mexican school system also suffers from overage, with many students enrolled in grades which are over the normative age that such grades serve. For example, the normative age of 9th graders (the last year of lower secondary school) is 14 or 15 for the generations not affected by the school entry-age reform in 2006. (For post-2006 generations, the age is 14 years old.). Figure 2.5 shows the percentage of those attending school at the age of 15 years by grade. At this age, the rule is two-thirds of these cohort should be attending 10th grade and the rest should be attending 9th grade. However, there are students who accelerated schooling which are less than 10%, and there are about 10% who are older than it is expected in grades below 9th.

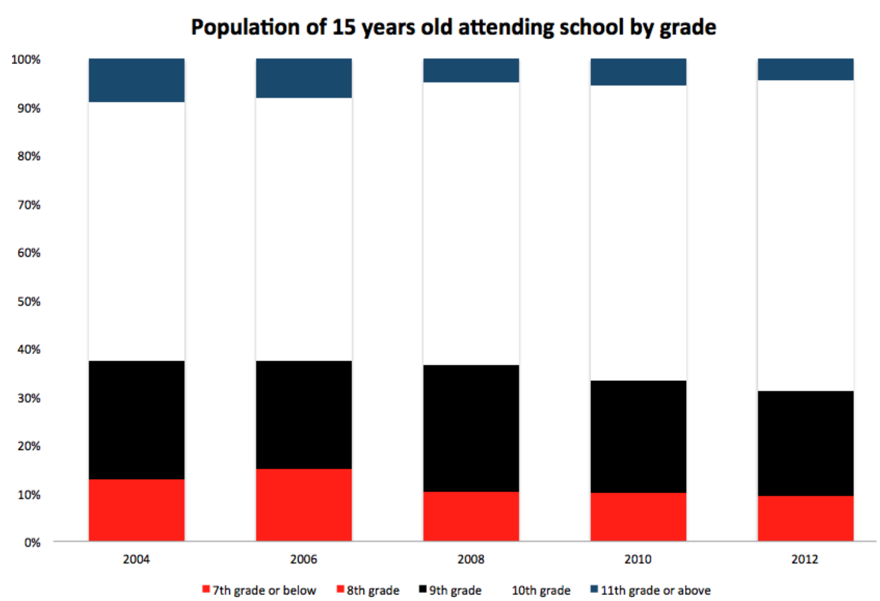

Figure 2.5: Population of 15 years old attending school by grade. Source:Author's calculation using ENIGH

Enrollment and graduation rates have increased overtime, especially for the most disadvantaged populations. In 1997, the Mexican government created a program that affords cash payments to low-income families in order for this segment of the population to enroll their children in basic education. The government created Progresa (now Oportunidades) to increase the education of the most disadvantaged families in México and has been successful in increasing enrollment in basic education for these populations. Oportunidades has had a significant impact on increasing schooling enrollment and attainment (Skoufias and Parker, 2001; Behrman et al., 2011; Todd and Wolpin, 2008). However, a lack of school quality has undermined the success of Oportunidades over the long run (Lunde et al., 2007).

How has this increase in enrollment affected achievement? How heterogeneous is achievement across subgroups of the population? To answer this question, Tables 2.2, 2.3 and 2.4 show the percent of students able to perform at the basic elementary level of math in 2006, 2010 and 2012 from the total population of that birth cohort eligible to attend 9th grade. The calculation uses the percentage of net enrollment (column 1-% enrolled) from the Mexican Household Survey (ENIGH) and the percent of 9th grade students who perform at least the at elementary level of math and Spanish comes from ENLACE (column 2 and 3 - Level 1- Math and Level 2 Spanish). Level 1 is the minimum learning level. Columns 4 (Math) and 5 (Spanish) are the percent of individuals of total population eligible to attend 9th grade who perform at least at the minimum learning standard.

In general, there has been an increase in average math learning over time, as measured by the results of tests scores at the 9th grade: a higher proportion of these students could perform basic, elementary (level 1) over time. The figures from 2006, 2010 and 2012 in Tables 2.2, 2.3 and 2.4 reflect this increasing math performance: 38% in 2006, 40% in 2010 and 43% in 2012 despite that net enrollment has maintained about 87 %.

In fact, those students attending a school in a very high marginality area show significant advances

Table 2.2: Measuring inequities in learning for the population in 2006

	% enrolled	Level 1-Math	Level 1-Spanish	Math	Spanish
Total	87.17	0.56	0.35	0.38	0.57
Girls	88.01	0.57	0.29	0.38	0.62
Boys	86.37	0.56	0.41	0.38	0.51
Very Low Marginality	90	0.52	0.27	0.43	0.65
Low Marginality	88.31	0.57	0.36	0.38	0.56
Medium Marginality	85.79	0.61	0.44	0.33	0.48
High Marginality	83.66	0.65	0.51	0.29	0.41
Very High Marginality	71.07	0.71	0.66	0.21	0.24
Indigenous	77.74	0.65	0.53	0.27	0.37
Non-indigenous	88.42	0.56	0.35	0.39	0.58
urban	89.6	0.57	0.36	0.39	0.58
rural	83.8	0.63	0.50	0.31	0.42

Source:Author's calculation using ENIGH 2006
Math and Spanish refer to at least elemental level

Table 2.3: Measuring inequities in learning for the population in 2010

	% enrolled	Level 1-Math	Level 1-Spanish	Math	Spanish
Total	87.11	0.54	0.38	0.40	0.54
Girls	88.86	0.54	0.32	0.41	0.60
Boys	85.41	0.55	0.44	0.39	0.48
Very Low Marginality	88.41	0.56	0.36	0.39	0.56
Low Marginality	88.55	0.56	0.40	0.39	0.53
Medium Marginality	87.89	0.54	0.41	0.40	0.52
High Marginality	83.60	0.50	0.39	0.42	0.51
Very High Marginality	75.30	0.53	0.47	0.35	0.40
Indigenous	85.31	0.52	0.41	0.41	0.51
Non-indigenous	87.30	0.55	0.38	0.39	0.54
urban	90.24	0.55	0.38	0.41	0.56
rural	83.08	0.53	0.41	0.39	0.49

Source:Author's calculation using ENIGH 2010
Math and Spanish refer to at least elemental level

at the basic, elementary level. In 2006, 71% of the population attended 9th grade and 21% of them performed at least at the basic level of math and 24% of them in Spanish. In 2012, these performance figures increased to 35% and 40%, respectively while enrollment for this population increased to 75 %. In fact, in 2012, the percentage of individuals attending school in a very high marginality municipality who performed at least at the elemental level close the gap to other marginality levels[1]. It is worth pointing out that the two states with municipalities with very high

[1]The National Population Council (Consejo Nacional de Población, CONAPO) ranks all localities according to a marginality index, a weighted average of literacy, access to basic public utilities, household infrastructure and average wages. Rankings range from very high marginalization, high marginalization, medium marginalization, low

marginality are Oaxaca and Michoacán and their ENLACE coverage is not representative. That is, there is an overestimation of these tables due to the absence of the of the worst schools from the database.

Table 2.4: Measuring inequities in learning for the population in 2012

	% enrolled	Level 1-Math	Level 1-Spanish	Math	Spanish
Total	86.35	0.51	0.41	0.43	0.51
Girls	87.98	0.48	0.34	0.45	0.58
Boys	84.80	0.51	0.50	0.42	0.42
Very Low Marginality	87.52	0.52	0.39	0.42	0.54
Low Marginality	83.70	0.51	0.43	0.41	0.48
Medium Marginality	82.87	0.49	0.45	0.42	0.45
High Marginality	88.70	0.45	0.45	0.49	0.49
Very High Marginality	85.99	0.45	0.52	0.47	0.42
Indigenous	85.99	0.47	0.45	0.47	0.48
Non-indigenous	88.72	0.51	0.41	0.42	0.51
urban	86.52	0.51	0.41	0.43	0.51
rural	86.13	0.49	0.46	0.44	0.46

Source:Author's calculation using ENIGH 2012
Math and Spanish refer to at least elemental level

Although the data presented here on learning outcomes shows significant changes over time, they also show that the percentage of students performing at very low levels in math and science remain at troublingly high levels.

México's participation in the OECD's first Program for International Student Assessment (PISA) confirms the challenges facing México in terms of school quality. PISA provides a measure of reading, mathematics and science achievement from a nationally representative sample, comparable across countries. PISA's assessment focuses on knowledge and skills to solve real-life problems and situations rather than on curriculum-based knowledge. Students from México are among the worst performers. Figure 2.6 depicts a linear association between average math scores in PISA 2012 and GDP per capita. This positive correlation is significant and suggests that those countries with greater GDP per capita tend to have higher PISA scores. However, even in comparison with

marginalization, and very low marginalization. For methodological details regarding México's marginality index, see http://www.conapo.gob.mx/

others with similar GDP per capita, México still performs at a relatively poor level, and also is among the worst performers in this test.

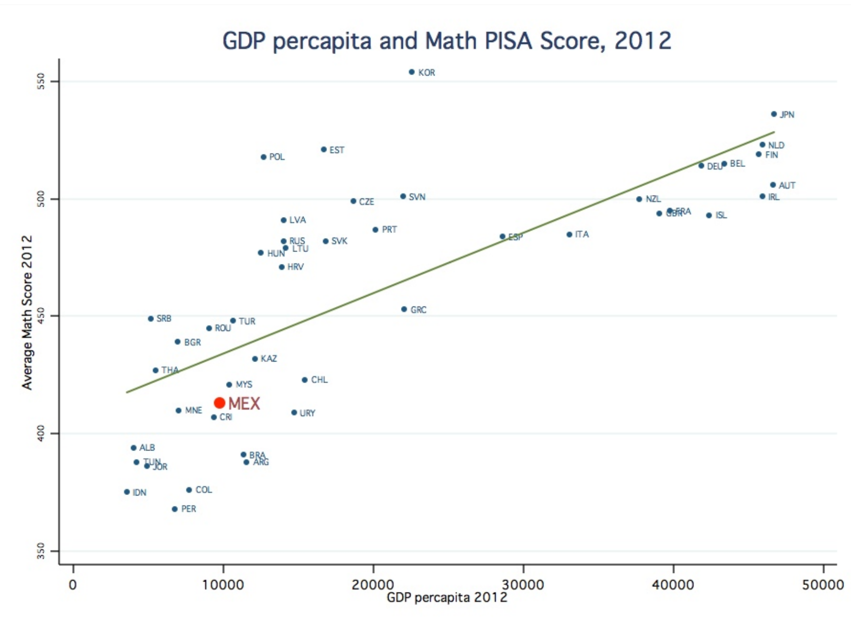

Figure 2.6: Average Math performance and Per-capita Income. Source:Author's calculation using PISA

Furthermore, analyzing the performance in PISA among Mexican states between 2003 and 2012, Figure 2.7 illustrates unequal performance across states and over time. The red lines indicate the average performance in both PISA rounds. There are four groups of states: The first group is Michoacán, Oaxaca and Sonora which did not participate in PISA 2012. Michoacán and Oaxaca were among the worst performers in achievement tests as well as other educational indicators. The second group consists of those below average in 2003 and below the average in 2012. Guerrero, Chiapas and Tabasco were the worst performers in both years at the left bottom corner of the graph. The third group is states with average performances in both years. Most states are in this category. Finally, the fourth group is composed of higher performers in both rounds of PISA—Aguascalientes, México City, Colima, Nuevo León and Querétaro. And though there is no data on any achievement test before decentralization, there are clear divergences in math achievement which exemplify long-standing inequalities across states.

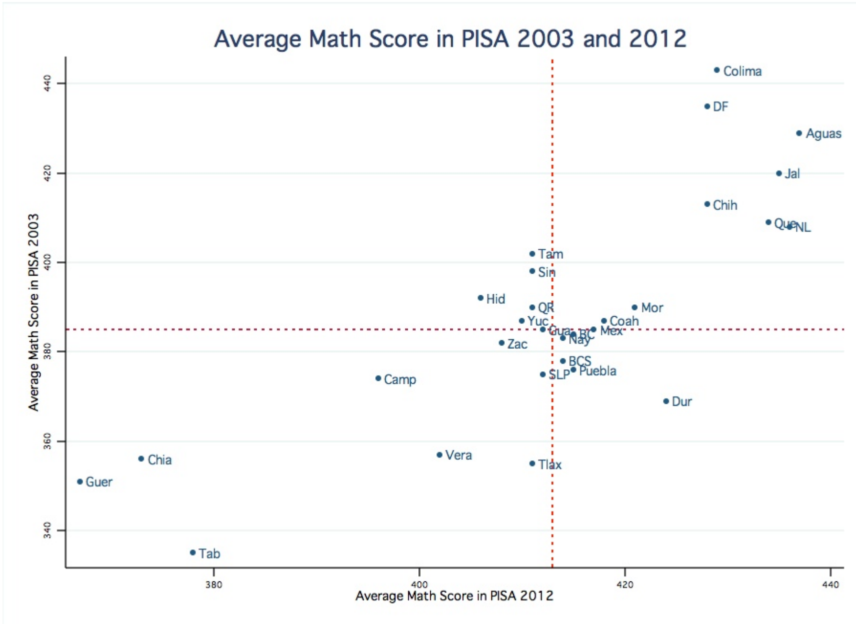

Figure 2.7: Math Performance across Mexican states in 2003 and 2012. Source:Author's calculation using PISA

2.4 Concluding remarks

In conclusion, despite the fact that México has achieved significant advances in terms of access and enrollment at all levels, the country faces serious challenges in moving the school system to high-quality standards, specially for indigenous and rural populations. The progress has been heterogeneous across states, and there remains persistent inequality among various Mexican regions.

2.4.1 Tables and Figures

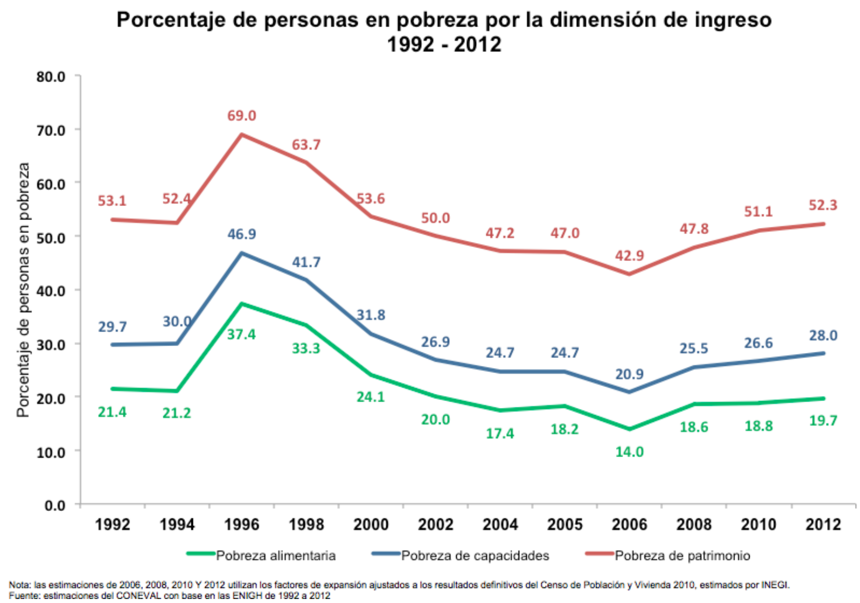

Figure 2.8: Poverty Evolution. Source:CONEVAL (2014)

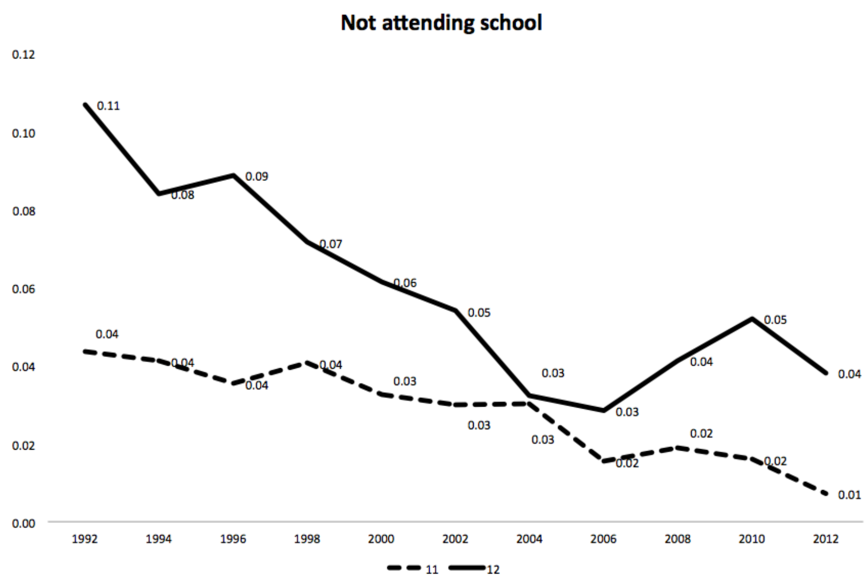

Figure 2.9: Percent of Individuals not Attending School by Age-Cohort.Source:Author's calculation using ENIGH

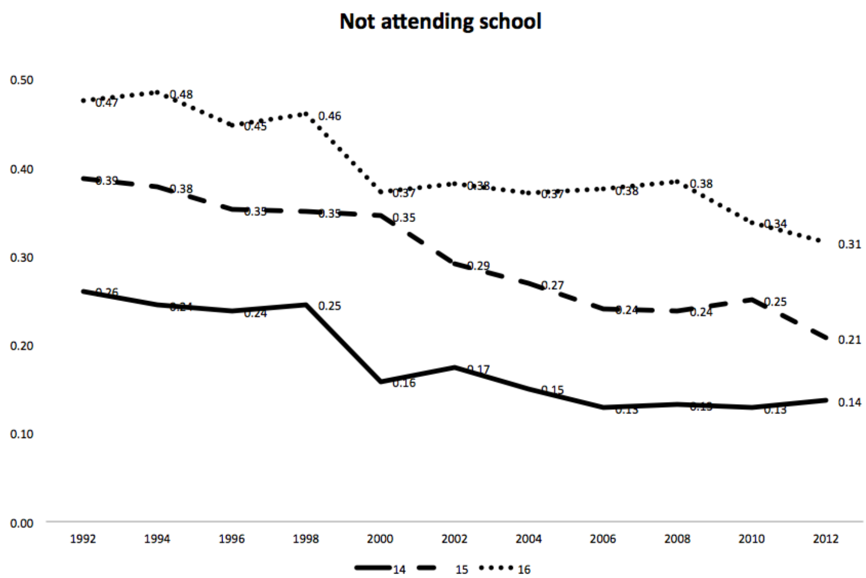

Figure 2.10: Percent of Individuals not Attending School by Age-Cohort.Source:Author's calculation using ENIGH

Table 2.5: Percent of children not enroll in education by age and school year

Age	1992	1994	1996	1998	2000	2002	2004	2006	2008	2010	2012
5	0.37	0.30	0.23	0.23	0.15	0.15	0.06	0.06	0.06	0.04	0.02
6	0.17	0.08	0.05	0.07	0.06	0.05	0.02	0.04	0.03	0.02	0.02
7	0.05	0.05	0.03	0.03	0.03	0.02	0.02	0.02	0.01	0.01	0.00
8	0.04	0.02	0.02	0.04	0.02	0.01	0.01	0.02	0.02	0.01	0.01
9	0.03	0.03	0.03	0.03	0.02	0.02	0.01	0.01	0.02	0.01	0.01
10	0.02	0.04	0.04	0.03	0.03	0.02	0.01	0.01	0.01	0.02	0.01
11	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.02	0.02	0.02	0.01
12	0.11	0.08	0.09	0.07	0.06	0.05	0.03	0.03	0.04	0.05	0.04
13	0.17	0.17	0.16	0.12	0.12	0.09	0.08	0.07	0.08	0.07	0.07
14	0.26	0.24	0.24	0.25	0.16	0.17	0.15	0.13	0.13	0.13	0.14
15	0.39	0.38	0.35	0.35	0.35	0.29	0.27	0.24	0.24	0.25	0.21
16	0.47	0.48	0.45	0.46	0.37	0.38	0.37	0.38	0.38	0.34	0.31

Source: SEP

Table 2.6: General Organization of the Mexican Education System

Type of Education	Level	Type of service
Basic Education	Preschool	Public - general
		Multigrade
		Indigenous
		Private
	Primary	Public - general
		Multigrade
		Indigenous
		Private
	Lower Secondary	Public - general
		Technical
		TV modality
		Private
Upper Middle Ed	Professional Tech	Public - general
	Upper Secondary	General
		Technical
		Private
Higher Education	Technical	Tech Universities
	University	Universities
	Graduate	Universities
		Research Institutes

Source: SEP

Chapter 3

Impact of the Programa de Atención Específica (PAE) para la Mejora del Logro Educativo in México (Program of Intensive School Focus for Educational Progress in México)

3.1 Introduction

There is an increasing tendency among policy makers to use information as a tool to improve the quality of education systems. Data used for accountability purposes is becoming an essential component of school system functioning (Bruns et al., 2011). School actors respond to accountability interventions in the form of rewards, sanctions and consequences—all intended to improve school quality. However, the evidence of the positive impact of such interventions on student performance is mixed (Rouse et al., 2013).

Often, accountability takes the form of interventions oriented to low-performing schools, as measured say by test scores. These education interventions that target poorly performing schools are themselves controversial. Some researchers argue that "bad" schools should not be "rewarded" with more resources and have challenged such program's "positive discrimination." On the other hand, it seems counterintuitive to withhold resources from a troubled school. And while there is some evidence that targeted interventions for ill performing schools help, there are few rigorous empirical studies on the effects of such programs.

Within México, the state of Colima has been a champion of accountability. Since 1997, Colima has had an evaluation system which publicly rewards the schools with the highest achievement rankings. In 2009, Colima's education authorities revised their accountability strategy and identified 108 schools that had obtained the lowest learning outcomes as measured by ENLACE. In early February 2010, the state governor announced the "performance status" of selected schools: Schools which performed below an arbitrary cut-off were automatically enrolled in a mandatory *Programa de Atención Específica para la Mejora del Logro Educativo* (PAE). Once identified as a PAE school, the school was required to implement a series of pedagogical interventions set by local authorities and consult with external advisors to assist in the preparation, collaboration and organization of a school improvement plan for a period of at least three years.

Exploiting PAE's rigid eligibility rule (an exogenously determined cut-off point dividing schools into treatment and control groups), this dissertation uses a regression discontinuity design to estimate the impact of the program. Participating PAE and non-participating schools were followed for three years to compare their performance.

In this way, the current study is part of the growing literature on the impact of accountability on school quality. This literature, however, has failed to separate the effect of the pedagogical or other interventions triggered by accountability on low-performing schools with the effect of being labeled or catalogued as a "failing" school. For while a failing status typically precipitates a series of explicit interventions in a school (more resources, pedagogical interventions, etc.), the impact of being labeled as "failing" could work through implicit mechanisms, such as stigmatization or reputation damage but also through the stimulus it may provide for coordinated collaboration among school actors to respond to the "failing" label.

The research in this chapter will seek to examine the overall effect of the PAE while at the same time identifying the impact of being labeled a "failing" school. The reason the present study can identify this labeling effect is because, despite the good initial intentions of policymakers, the PAE program was halted early, even before the government assigned any additional resources to the schools so that reforms could be implemented. Any short-run impact in the schools would have been connected to the mere classification and announcement of the schools as "failing," and any longer-term effects would have been because of pedagogical changes made by the school staff at that time, without any support from the government, which had terminated the program.

The following section, Section 3.2, summarizes the current literature relevant to interventions targeting low-performing schools, identifying some weaknesses that the current study will seek to address. Section 3.3 provides background information on the Mexican state of Colima, describes the PAE and charts some trends in learning outcomes. Section 3.4 details the methodology and identification strategy while Section 3.5 discusses the main results. Finally, a concluding Section 3.6 enumerates some policy recommendations.

3.2 Related Literature

In a world of scarce resources, policymakers often confront limited options to improve student learning. One strategy is to rely on socioeconomic background and allocate additional resources to schools serving underprivileged students. These targeted programs are motivated by the fact that schools where children of families with low socioeconomic background enroll are also the schools most likely to have the poorest student outcomes. Research on programs that target schools based on student socioeconomic background is limited, and has produced mixed results.

From the Netherlands, the effects of two subsidies targeting schools with large proportions of disadvantaged pupils have been evaluated (Leuven et al., 2004). The first subsidy scheme gave primary schools with at least 70% disadvantaged minority pupils extra funding for school personnel. The second subsidy scheme gave primary schools with at least 70% pupils—from any disadvantaged group—extra funding for computers and software. A regression discontinuity design was used to estimate these effects within a local difference-in-differences framework. The evaluation indicated negative results for both subsidies—with some outcomes significantly different from zero.

In the United States, Title I aims to overcome educational disparities associated with poverty so as to ensure that all children meet state academic achievement standards. The Title I program provides additional resources to schools with high poverty rates through funding for school-wide programs or for targeted programs for disadvantaged students (if they compose less than 40% of the school population). While most of the funds from the program are utilized for instruction-related expenses almost half of the funds were spent on salaries and benefits (Stullich et al., 2009). And results have been mixed. Various evaluations have revealed some positive effects, but in most cases these benefits are short-term gains, and in some cases, even negative results were found (Slavin, 1989; van der Klaauw, 2008)

A different strategy does not use socioeconomic disparities as a proxy to focalize educational programs. Instead, standardized test scores are used to help identify which schools need additional resources so as to create a more equitable education system (McKinsey & Company 2007). That is, improving the performance of lagging schools in terms of test scores improves the system as a whole and reduces differences between low- and high-performing schools. There are an array of such programs, but their effectiveness is yet to be fully vetted. Generally speaking, there are two types of programs which fall under this strategy: educational interventions which target low-performing schools and accountability schemes which provide performance-based incentives and/or penalties.

With respect to the first type of intervention, several remedial programs attempt to address achievement disparities through a combination of interventions which include, for instance, greater resources and technical assistance. The P-900 program in Chile is such a program. Introduced in 1990, P-900 is a program of four interventions targeted at low-performing, publicly funded schools. Schools received improvements in their infrastructure and were given a variety of instructional materials. Teachers attended weekly training workshops, and after school-tutoring workshops were created. Chay et al. (2003) concluded that the P-900 program in Chile had positive and significant effects on test score gains (albeit much smaller than those found by Tokman (2002)'s double difference estimates).

By contrast, the second type of intervention imposes a regime of accountability that pressures low-performing schools to improve test scores, under the threat of penalties which may include the closing of the school. One of the most prominent examples of accountability is the state-level accountability and ranking system of No Child Left Behind in the United States. There is some evidence that schools respond to accountability pressures with improved test scores (Carnoy and

Loeb, 2003; Hanushek and Raymond, 2004). Indeed, the research shows that students in high-accountability states averaged significantly greater gains on 8th grade math test than students in states with little or no state measures to formally track student performance. In addition, other interventions focusing on accountability in other contexts have resulted in increased average test scores (Rouse et al., 2013; Rockoff and Turner, 2008; Carnoy and Loeb, 2003). In fact, the overall effects of accountability systems range from test score increases of 20% to 40% in standard deviation (Hanushek and Raymond, 2004) (though estimates are generally smaller when focusing on the specific impact of sanctions on failing schools (Figlio and Rouse, 2006). In a meta-analysis by Lee's (2008) the average effect size of this kind of intervention is 0.08 S.D.

Beyond education, accountability schemes have also proven to increase quality of service in other fields. Bevan and Wilson (2013) show that prior to devolution in 1999, the governance of schools and hospitals in England and Wales was similar. After devolution, their funding and organization continued to be similar, but the two governments adopted different policies in the pursuit of common objectives. This resulted in two natural experiments of policy change. A governance model of so-called "trust and altruism" in Wales actually resulted in poorer performance relative to England. Bevan and Wilson (2013) argue that the English policy of public "naming and shaming" resulted in improved examination performance and helped to mitigate an endemic problem of long waiting times. Analogous results have been obtained in the restaurant business: The public display of hygiene quality report cards in restaurant windows obtained from health inspections have forced restaurants to improve their health scores (Jin and Leslie, 2003). Such accountability pressures work not only for schools, governments and businesses, but individuals too. By providing peer comparisons feedback to customers on their home electricity and natural gas usage individuals reduce their consumption (Ayres et al., 2012).

There is, then, good reason to believe that schools are also sensitive to transparency accountability. In the Netherlands, both average grades and the number of diplomas awarded increased after schools received their own negative report cards. For schools that received the lowest ranking, the one-year short-term effects on final exam grades amounted to 10% to 30% of a standard deviation (Koning and van der Wiel, 2013).

Moreover, identifying schools as low (or high) performing has a direct impact on school choice, and this too has been investigated. In the Netherlands, Koning and van der Wiel (2013) found that school-quality scores impact the number of first-year students who choose a school. In the United States, Hastings and Weinstein (2008) analyzed an experiment in which parents of students at low-performing schools were provided information about the quality of alternative schools. They found that the provision of explicit quality information led more parents to choose higher-scoring schools at rates 5% to 7% higher. In this way, we know that not only do schools respond to school-quality information, we know that parents do too.

Despite the positive association of accountability with improved student outcomes, such feedback-based interventions do complicate estimations of causality. According to the education production function, student performance is a function of family resources and family choices which partially determine school inputs (Todd and Wolpin, 2003). For this reason, using student achievement (in the form of test scores) to rank school performance will cause school rankings to correlate with family resources (as well as school inputs). Mizala et al. (2006) show that the distribution of test scores in Chile is largely an expression of socioeconomic status. In this way, the impact of accountability is itself a function of socioeconomic conditions.

And there are other issues to consider. Transitory noise in average scores and mean reversion lead conventional estimation approaches (such as a difference-in-difference), to overstate the impacts of such accountability programs. In particular, Chay et al. (2003) identify mean reversion as a serious limitation to Tokman (2002)'s evaluation of P-900. Schools can respond to accountability pressures by misreporting performance measures or engaging in tactics that increase scores at the expense of real learning (e.g., teaching to the test, shaping the testing pool, cheating) (Reback and Cullen, 2006; Figlio and Getzler, 2002; Jacob and Levitt, 2003).

How, then, have Mexican schools actually responded to the PAE program? One factor to consider is the fact that the PAE program was discontinued only after one year of implementation. This means that only interventions related to the program's preparation were enacted and partially implemented. Activities during the preparation period included notifying the school of its poor quality, identifying the school's main challenges, and developing a plan to address those challenges. The PAE information, then, amounted to a detailed diagnosis of a school's problems coupled with an invitation to network with other school directors, teachers and advisers to develop improvements—no additional inputs to the schools were actually funded or provided. In this way, the current study examines how using standardized tests scores to identify poor performing schools, diagnosing the school problems and developing school reforms may –by itself– lead to higher student performance. The impact will be examined in two time contexts: the immediate effects of the PAE, through its labeling and informational aspects, and its longer-run effects, which may have occurred through pedagogical and internal changes made by the school staff itself (without help from the government, which had officially terminated the program). If it turns out that the PAE, as implemented –purely as an informational program—does improve student achievement, it would suggest that schools can capitalize on just the purely informational aspects of accountability –and the changes this generates at the school level–to improve quality, without necessarily requiring extensive government support in the form of additional resources.

But how does the mere availability of information about school quality affect school performance? One way that the informational aspect of accountability results in improvement is that it creates a fact-based dialogue among educational authorities, directors, school principals and teachers. As plans are developed based on the information low-performing schools receive about their failures, interventions can then be designed that impact directly on student achievement. In this way, identification is not only the first step toward improvement, it is arguably the most impactful step. In fact, identification of the problems a school has may not only be necessary, but could be surprisingly sufficient; improvements can take hold in a school even before additional school inputs have been applied.

Given the fact that the PAE was terminated after the preparatory, informational part of the project was completed, this allows a careful study of the impact that the informational aspects of an accountability regime can have on student outcomes, even if the regime does not involve increased resources or any specific, targeted interventions. Research on the PAE is also significant because there is very little rigorous impact evaluation analysis of programs that target low-performing schools in México and so there is very little evidence about the impact of such programs on learning outcomes. Hence the present paper will close an important gap in the literature.

3.3 Background, PAE Description and Recent Trends

Colima is a small state in the center-west region of México with a population of 650,555 inhabitants, 34.3% of whom live in households with incomes below the official 2012 poverty line. (The poverty headcount ratio in México is 45.4%.) Since the decentralization of May 1992, Colima has built an efficient school administration and adjusted its educational programs to the specific characteristics and needs of its region. Indeed, throughout the 1990s, Colima experimented and innovated with its educational system. In 1998, for instance, Colima created a mandatory program of school-based management named Programa de Gestion Escolar for all schools (except private) in the state. In 2002, this Colima-inspired program was launched at the national level with grants for the poorest Mexican schools. This national program required not only that schools participate but also submit a plan in order to win additional grant funding. Also, the selection mechanism failed due to the lack of data to select the poorest schools.

By 2003, Colima was outperforming all Mexican states in math, reading and science—and actually approaching OECD averages. For example, Colima's math scores were on par with those for Greece and Serbia, higher than those from Thailand, Brazil, Uruguay and Turkey. In PISA 2006, Colima decreased its performance but ranked among the top five states with the same results in PISA 2009 and 2012.

Colima soon became a pioneer in México for disseminating school performance data (e.g., rankings and rewards). This comprehensive and efficient data system included student-level records which could be disseminated within the school as well as externally to parents, the community and the media. In the late 1990s, Colima also launched Concurso de Escuelas de Calidad (CEC, Contest of Quality Schools)—a public event organized by the state governor to recognize the best performing schools. Using a series of achievement tests administered to grades 3 to 9 in all types of schools (e.g., private, public, and rural), the governor awarded approximately \$3,000 to the winner among each of six subgroups: 1) private schools, 2) public urban, 3) poor public urban, 4) public semi-urban, 5) rural complete school and 6) rural incomplete school (multigrade school).

Colima's state-run assessment program (using local assessment instruments) was eventually eclipsed by the national ENLACE exam. In the school year 2005-2006, for the first time, the Ministry of Education applied a census achievement test named ENLACE. An exam designed to gather information on students' performance, ENLACE involves tests in Math, Spanish and a rotative subject for third, fourth, fifth, sixth and nine grade. ENLACE was not a high stakes exam until the school year 2010/2011. But it won popularity due to the increased flow of information between schools, parents and the community. In early October of 2009, the results from ENLACE were released, and Colima performed under the National average. All the schools in Colima had access to the ENLACE information but there is no evidence of rankings or public dissemination of the results at this stage. That year, the Colima's Ministry of Education (CMOE) started the design of PAE; at the same time, a national program with the same characteristics started to be designed as well. Colima has adapted several Federal-run programs to be more relevant to the local context. PAE is one of such programs. PAE shares the objectives and some elements of its design with the Federal Program "PEMLE". Although targeting criteria between the two programs differs only marginally, PAE adds a more detailed diagnosis and close follow-up of the school improvement plan vis-à-vis PEMLE (for a more precise comparison of PAE and PEMLE see Annex 1). There is no documentation if PAE was part of a Federal Program or it was created parallel to a Federal program, however, the focus and the content of both programs differ. The National program, "PEMLE" , also used ENLACE 2009 to select the schools but had a more elaborated selection of schools which included trends overtime with no rankings (for more details see the annex). Also, PEMLE did not enforce participation and allowed states to include schools on a discretionary basis, it was a program with no stakes, no rewards and no consequences.

3.3.1 PAE Description

PAE was a program designed to improve learning outcomes among the lowest performing public primary schools in Colima. While there still remains some debate regarding the reliability of standardized test scores as measures of school performance (Kane and Staiger, 2002), the Colima Ministry of Education used 2008-2009 ENLACE score data to construct its ranking of schools.The program's operation guidelines excluded multi-grade schools with one or two teachers and community schools regulated by the "Consejo Nacional de Fomento Educativo", CONAFE.[1].

Of the 477 primary schools in Colima in academic year 2008-2009, 40 were private, 39 belong to CONAFE, 38 and 40 were one- and two-teacher schools, respectively and 10 for a variety of reason, did not have an ENLACE score. The group of PAE-eligible schools consisted, then, of 310 public primary schools (see Figure 3.1) with a total student population of 62,366 (95.17% of the total number of students in public primary schools in Colima during the 2008-2009 school year).

Between October and November 2009 the CMOE used the 2008-2009 ENLACE score data to construct its ranking of schools. School scores were a simple average of the three subject areas tested: math, Spanish and science–across grades 3, 4, 5 and 6—and schools in the 35th percentile or less of the distribution of school performance were selected as PAE schools. As shown in Figure 3.1, PAE included 108 of the 310 schools that belong to the potentially eligible population.[2] The PAE schools were distributed across all ten municipalities of Colima and encompassed 1,535 teachers and a total of 26,943 students.

Figure 4.2 illustrates the timeline followed by the design and implementation of Colima's PAE. Between October and November 2009 the CMOE selected the schools that were going to participate in PAE following the criteria described above. In January 2010 the selected schools were officially notified. In February 2010 at a teachers' congress in Colima, the Governor launched the program and publicly disseminated the list of selected schools. Although the selected schools were presented as those with lowest learning outcomes in the state, the Governor emphasized the co-responsibility behind low performance of schools and state education authorities and the importance of working together to achieve improvements. Between the public announcement of PAE

[1]For details on CONAFE see www.conafe.gob.mx

[2]Two schools were dropped from the sample due to a mistake in their original classification as non-multigrade schools which later on was changed to multigrade.

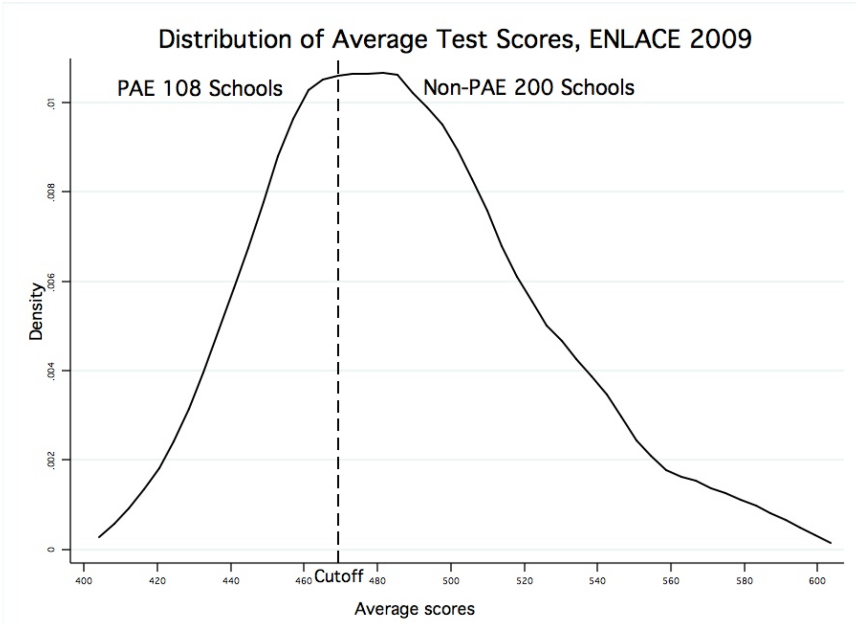

Figure 3.1: PAE and Non-PAE Population and Sample

and the first follow up ENLACE test in May of 2010, PAE schools were assigned a technical adviser who had to visit the school three times a month to work with school directors and teachers in the diagnosis of the ENLACE test and the design of improvement strategies. In addition, the PAE technical adviser coached teachers on analyzing the ENLACE information to have a clear understanding of how schools were selected into PAE and the causes of poor performance within their schools. This first four months of PAE, which the CMOE called the "awareness" period, was too short to change any of the fundamental inputs of the learning production function and it is hence capturing the "accountability" effect of the program.

Speaking generally, PAE public announcements did explicitly emphasize the shared responsibilities between state authorities and the schools and also probably implicit mechanisms (as verbal complaints, stigmatization, reputation damage); that is, there was a policy dialogue with treated schools which implied collective action and made school actors' efforts more accountable. In addition, state education authorities coached teachers on analyzing the information used to selected schools and diagnosing the causes of poor performance within their schools. [3]

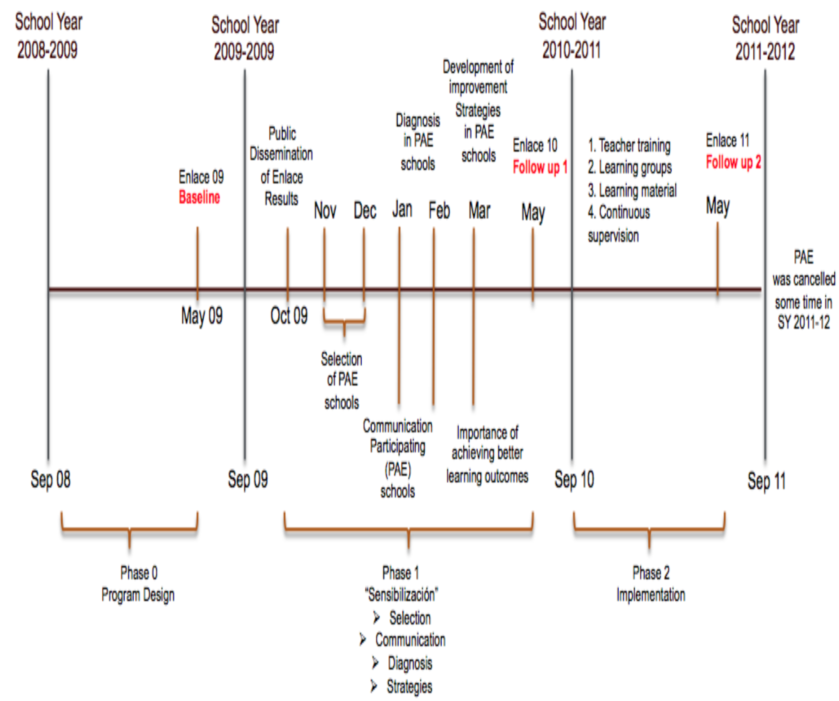

Figure 3.2: The timeline of the PAE

Between May and June 2010, authorities at Colima's Ministry of Education, together with school directors and selected teachers, developed a simple methodology to construct a detailed diagnosis identifying the learning weaknesses of their students based on the ENLACE results.[4] The diagnoses were tailored to each school: the ENLACE test questions which more students answered wrong were collected by subject area, grade and classroom. Using personal identification numbers and a password, all teachers in México had online access to a rich data base organizing the proportion of students in their class who answered an ENLACE question incorrectly. The website

[3] In addition, a consultant firm visited all PAE schools to document the students', teachers', parents' and principals' opinions about their schools. The main objective of these qualitative reports was to identify the causes of the poor ENLACE performance among these PAE schools in 2009. The main findings were that the low socioeconomic status of the students coupled with dispirited attitudes among teachers had a detrimental affect learning. In fact, one key observation in the report was that teachers in PAE schools had the same level of credentials than non-PAE teachers. The teachers did not differ in formal education and training; the teachers differed in personal passion and conviction. Delivered in early May 2010 to the Colima Ministry of Education, the pedagogical recommendations of the PAE were implemented starting in the 2010-2011school year

[4] The methodology relied on public information constructed by the Federal Ministry of Education (SEP).

also indicated what area of knowledge and the relevant curriculum for each ENLACE questions thereby providing teachers a concrete pedagogical direction to guide their efforts.

The second phase of PAE started in September 2010 and consisted of pedagogical interventions and the monitoring of progress and implementation. With diagnoses in hand, state authorities, school directors and teachers collaboratively designed school-specific improvement strategies, which, broadly speaking, included one or more of the following four interventions:

1. Strengthening school-based management. This intervention draws on the experiences gained from the previously implemented PEC (*Programa Escuelas de Calidad*) and AGES (*Apoyo a la Gestión Escolar*).

2. Redefining the role of school supervisors and training them. School supervisors in México are not appointed through a competitive process and do not have to undertake any training before taking on their duty. Hence, there is a high degree of variation in the quality of school supervision.

3. Redefining the role of school directors and training them. Similar to school supervisors, many of the school directors lack the skills necessary on how to manage a school. Directors have trouble identifying the strengths and weaknesses of their school and based on this design a school plan for the medium- and long-term. Directors seldom set measurable and reachable goals in crucial indicators to monitor progress, among others.

4. Reinforcing teachers' knowledge in the identified academic areas posing challenges. The program provided teachers with training and special courses to strengthen their knowledge in subject areas identified as challenging during the diagnosis step of the program.

Table 3.1: Evolution of Average Math Score in Colima based on ENLACE

year	All Schools	Non-PAE	PAE
2006	485	500	459
2007	497	514	467
2008	490	506	461
2009	488	507	451
2010	503	517	475
2011	528	544	500
2012	514	529	487
2013	527	542	500

Source: Author's elaboration using ENLACE, SEP

Due to reasons that have little, if anything to do with the program's performance, PAE was cancelled sometime between October and December 2011.

3.3.2 Dataset and Recent Trends

This study uses and merges student learning outcomes as measured by ENLACE with administrative school census data collected by federal and state education authorities (known as the *Formato 911*). Since 1998, this school census is collected at the beginning and end of each school year, and lists, among other entries, the number of teachers, students, classrooms, computers, average years of education among teachers as well as the geographic location for each school. In virtue of a unique school identifier (*Clave de Centro de Trabajo, CCT*), it is possible to merge this school census data with the results from standardized ENLACE tests into a single data base. In addition to learning outcomes, ENLACE includes socioeconomic information for each school based on their geographical location.[5]

[5]The National Population Council (Consejo Nacional de Población, CONAPO) ranks all localities (an administrative and / or geographic entity often more disaggregated than a municipality) in México according to a marginality index, a weighted average of literacy, access to basic public utilities, household infrastructure and average wages. Rankings range from very high marginalization, high marginalization, medium marginalization, low marginalization, and very low marginalization. For methodological details regarding México's marginality index, see http://www.conapo.gob.mx/

Table 3.1 depicts mean math scores in Colima from 2006 to 2013. In general, schools in Colima have improved by about 42 points throughout this period. As expected, the 108 PAE schools had lower learning outcomes relative to the non-PAE schools. In 2006, PAE schools were 41 points lower than non-PAE schools and in 2013, PAE schools were still 42 points behind non-PAE schools, in other words, score gains among PAE schools were similar to non-PAE schools throughout this period. In 2009, the baseline year, the difference between PAE and non-PAE schools was 56 points and the gap was reduced to 42 point the year after, perhaps partly explained by mean reversion effects (see Chay et al. (2003)).

3.4 Methodology

The literature in economics of education has used educational production functions to estimate the relative impact of various factors affecting student outcomes. One can utilize, therefore, an education production function (EPF) approach to estimate the impact of policy interventions on student outcomes. Endogeneity and causality issues, however, require that the statistical analysis employ methods that adjust for the potential biases obtained through OLS estimation. In this dissertation, an EPF is estimated to examine Colima's PAE adopting a quasi-experimental evaluation design, which mimics a randomized experiment, and allows the parameter relevant for policy analysis to be more accurately estimated. The total effect of the program (which includes both direct and indirect effects) is defined as the local average treatment effect on achievement for students (Todd and Wolpin, 2003).

A school's eligibility for PAE was first determined by ENLACE scores. This exogenous classification created two groups: schools just below and schools just above the exogenous threshold. Under these conditions, a discontinuity in the relationship (or regression) between pre-PAE scores and post-PAE scores will reflect the impact of the PAE program (Imbens and Lemieux, 2007; Imbens and Wooldridge, 2008).

A simple comparison of mean test score differences between PAE schools and non-PAE schools over time (see Table 3.5) or a difference-in-difference estimation may be too na ive. First, factors unrelated to the program can impact both groups, and might cause the impact of the PAE to be over- or underestimated. For example, the discussion in Mizala et al. (2006) suggests that school rankings issuing from repeated cross-sections of Chile's achievement data are not necessarily indicative of school effectiveness but are simply reflective of the socioeconomic composition of its students. Second, the selection of schools on the basis of a one-year school performance ranking may misclassify schools due to a one-time performance aberration (caused by one time shocks to non persistent causes or mean reverting noise). As discussed by Chay et al. (2003), this could bias estimators of the program's impact since PAE's (low-performing) schools would tend to automatically revert to the overall mean. A double difference approach could, therefore, mistakenly attribute score improvements to the program.

Following Chay et al. (2003), a regression discontinuity design can defuse this mean reverting problem. The logic behind their approach is quite simple: The objective is to identify a group of schools that are part of PAE that are similar enough to a group of schools that is not part of the program. A good place to identify such comparison groups is right around the cut-off point distinguishing PAE from non-PAE schools as the threshold mimics a randomized selection to receive or not to receive treatment. An important limitation to this sort of regression discontinuity design, however, is that the results are valid only for observations around the cut-off point; the estimated impact is limited to a local average treatment effect (LATE) which cannot be generalized to cover the entire population, thereby undermining the external validity of the estimation. This shortcoming, however, is not debilitating. Since PAE is a targeted program, the fact that its results are not valid for all populations is not especially relevant. The regression results are intended to inform the evaluation of this PAE program and related public policy issues.

The regression discontinuity approach is used to answer the following research questions:

(i) Does PAE increase learning outcomes among participating schools?

(ii) If there is an impact, how long does the effect persist over time?

(iii) What role does mere identification, disclosure and discussion of a school's problems, which was the main impact of PAE, when it was stopped, play in effectuating improvements?

(iv) Does PAE have a differential impact on student achievement distributions?

(v) Does PAE improve the management of school directors?

More formally, the following equation specifies the educational production function utilized to examine the effects of PAE on student achievement. Let us define $Y_{i,s,t}$ as the average ENLACE performance of student *ith* in school s and year t as a function of a dummy variable PAE, taking the value of one if the school is part of PAE, zero otherwise; ENLACE average results at the baseline $Y_{s,2009}$; the interaction between the former and the later; and a series of school-level controls $X_{s,t}$:

$$Y_{s,g,t} = \beta_0 + \beta_1 PAE_s + \beta_2 Y_{s,2009} + \gamma PAE_s * (Y_{s,2009}) + \sum_{k=3}^{K} \beta_k X_{s,t}^k + \eta_s + \nu_{s,t} \qquad (3.1)$$

Notice that the dummy variable identifying schools belonging to PAE is based on eligibility to the program, determined by ENLACE average results for 2009. By assumption $\varepsilon_{i,s,t}$ should be independently and identically distributed (iid) with a mean of zero and known variance. However since the unit of intervention is the school but the unit of analysis is the student (i.e. schools and not students are assigned or not to PAE), the unobservables are defined as composed of two terms $\varepsilon_{i,s,t} = \eta_s + \nu_{i,s,t}$. In other words, the unobservables are captured by two components, a school-specific one (η_s) and an individual-, school- and time-specific term ($\nu_{i,s,t}$). This structure of the error term implies clustering of students within schools allowing for intra-school correlation across students. Equation 3.1 can be modified to include higher order terms of the "forcing variable" $Y_{s,2009}$ to control for non-linearities in the relationship between the eligibility criteria and subsequent learning outcomes.

For a group of schools sufficiently close to the PAE-eligibility cut-off, such that samples are balanced both in observables and unobservables, the effects of PAE will be captured by $\hat{\beta}_{3,t}$ in Equation 3.1. Since PAE was announced in February of 2010 and the first follow up ENLACE test was a few months after in May of that same year, the parameter estimating the discontinuity $\hat{\beta}_{3,2010}$ captures immediate the accountability effect of the program while that for 2011 and 2012 captures also the effects of an additional pedagogical and other interventions adopted by school afterwards. A variation of Equation 3.1 can be used to test for heterogeneity across subject areas. Additionally, a more disaggregated version of Equation 3.1 can be used to test whether the effects of the program are heterogenous across the distribution of ex-ante test scores. In other words, by estimating Equation 3.1 separately for groups of students located at different levels of learning outcomes, it can be shown if, say, increases in test scores are occurring among students with relatively high initial learning outcomes in poor performing schools.

3.4.1 Determining the bandwidth

The optimal number of schools around the cut-off by which to evaluate the impact of the PAE program is determined by a trade-off between precision and internal validity. That is, a narrow bandwidth would select schools very close to the cut-off hence more similar in observables and unobservables, but the statistical power might be compromised given a small number of observations. On the other hand, a wider bandwidth would increase the number of observations in the treatment and control groups but might not yield balanced samples in observables (and unobserv-

Table 3.2: Bandwidths around the cutoff

Enlace Points	Schools	Students	PAE	NonPAE
4.74	38	4,069	22	16
9.48	66	7,422	35	31
18.97	122	13,353	59	63

Source: Author's elaboration using RD command

ables). Following Imbens and Kalyanaraman (2009), the optimal bandwidth is determined to be 9.48 ENLACE points below and above the cut-off or 0.0948 standard deviations around the threshold dividing PAE from non-PAE schools. This optimal bandwidth will be complemented with two alternative rather arbitrary ones: half of the optimal bandwidth (±4.74) and double the optimal bandwidth (±18.97).[6] Table 3.2 shows the number of schools above (non-PAE) and below (PAE) the cut-off as well as the number of students using the three different bandwidths.

Figure 3.3 shows the intra-class correlation for those schools around the cut-off. This coefficient is zero until 15 points after the cutoff, and less than 0.02 at 25 points around the cutoff. This confirms that a comparison between schools can be conducted for the suggested bandwidths.

[6] The optimal bandwidth was computed using the regression discontinuity Stata program RD.

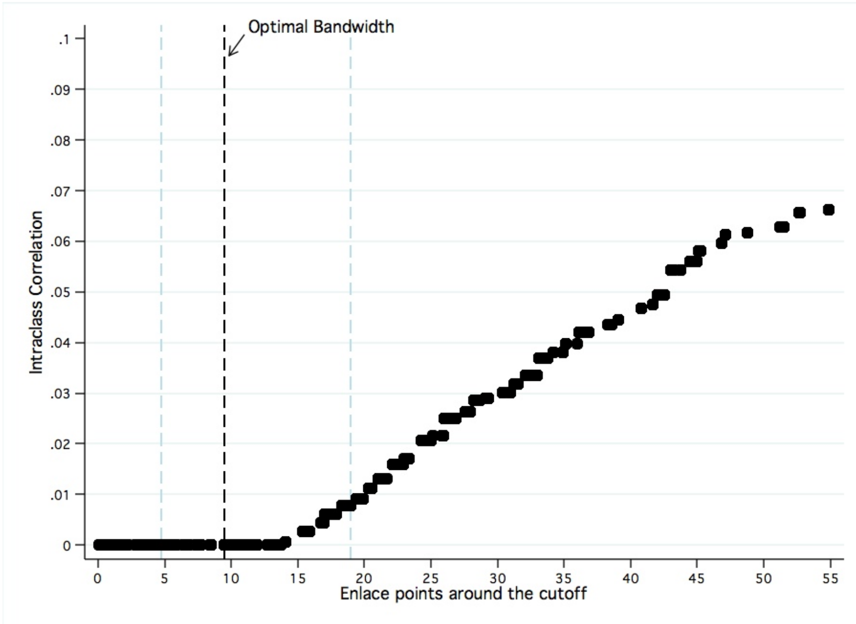

Figure 3.3: Intraclass Correlation coefficient around the cutoff

To create a comparison between the PAE and non-PAE schools, 80 schools were chosen before the program started. In a ranking where 1st place indicates the lowest scoring school, schools ranging from 70 to 108 would be chosen as the PAE treatment group while the non-PAE control group would consist of schools 109 to 148. This procedure allows the use of a regression discontinuity to estimate the impact of the program. Figure 3.10 shows the density of the assignment variable and the densities for both groups (PAE and non-PAE schools). The straight line is the cut-off which divides the two groups, and the density function appears continuous around the bandwidth. In this way, there is no pattern which would invalidate the identification strategy.

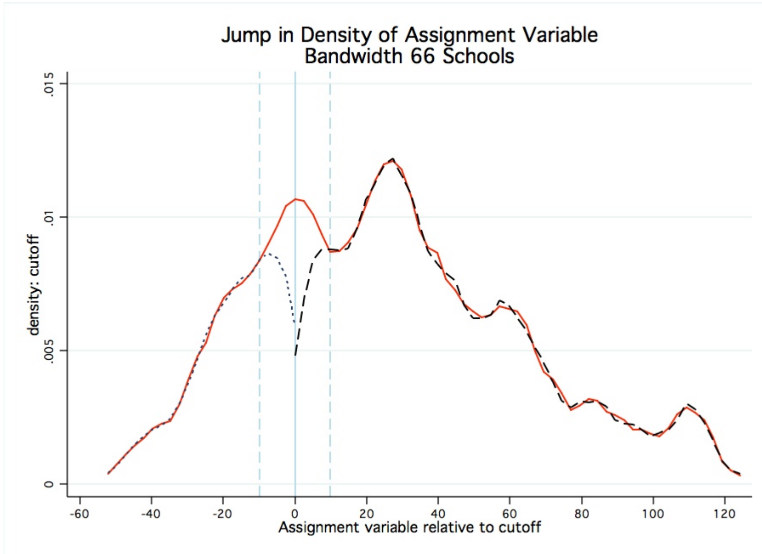

Figure 3.4: Density of the assignment variable

3.4.2 Sample Balance

If as the PAE treatment and control groups are equal in expectation in terms of observed and unobserved dimensions, then the evaluation framework will mimic a randomized experiment. Table 3.3 summarizes the descriptive statistics for a sample of 4th graders in the PAE and non-PAE schools. While there are no significant difference in age, sex and access to the Oportunidades program, there are some slight differences in parental education, family size, and Internet access at home do arise. Although relatively minor, the discrepancies suggest that students in the (control) non-PAE schools are slightly richer than the (treatment) PAE schools.

Having first verified that there are no major differences in socioeconomic background between the treatment and control groups, an analysis of school inputs was also done. The school inputs for the 2008-2009 school year, before treatment, are shown in Table 3.4: as can be seen, the school inputs –such as school size and students pre teacher–are not significantly different across treatment and control.

Table 3.3: Descriptives statistics of fourth graders in the evaluation sample (78 schools)

Variable	Non-PAE control	S.E.	PAE-Treatment	S.E	Difference	S.E.
Age	10.0	0.020	10.1	0.020	0.0	(0.028)
Female	0.5	0.015	0.5	0.015	0.0	(0.021)
Oportunidades	0.4	0.014	0.4	0.015	0.0	(0.021)
Years in preschool	2.74	0.029	2.60	0.029	0.14	(0.041)**
Live with parents	0.74	0.013	0.75	0.013	0.00	(0.018)
Mother's education	9.48	0.165	8.98	0.148	0.50	(0.222)**
Father's education	9.94	0.185	9.12	0.174	0.82	(0.253)***
Number of siblings	2.31	0.048	2.48	0.050	-0.17	(0.069)***
Cars at home	0.92	0.027	0.91	0.027	0.01	(0.038)
Internet at home	0.38	0.014	0.33	0.014	0.05	(0.020)***
Computers at home	0.62	0.024	0.62	0.025	0.00	(0.035)
Observations	1,104		1,148			

Source: Student-PAE Survey

Table 3.4: School Inputs 2009, evaluation sample

	Non-PAE control	PAE-Treatment	Difference	S.E.
Number of students	197	191	5.97	(21.30)
Number of teachers	7.87	7.77	.099	(.728)
% of teachers with Incentive Program	0.49	0.40	.08	(.070)
% of teachers with B.A. or more	0.68	0.78	-0.10	(.06)
Student/teacher ratio	24.65	24.44	.21	(1.12)
Intra school year dropout	0.2%	0.2%	0.00	(.009)
Students who fail the grade	0.03	0.03	0.00	(.006)

Source: School Census, 2009

To show diagrammatically and in more detail the comparison between PAE and non-PAE schools, Figure 3.5 shows the continuity of the drop-out rate along the 2009 average achievement, the forcing variable. The continuity of the covariate indicates that the treatment and control were equal in expectation in terms of the student composition of the two groups.

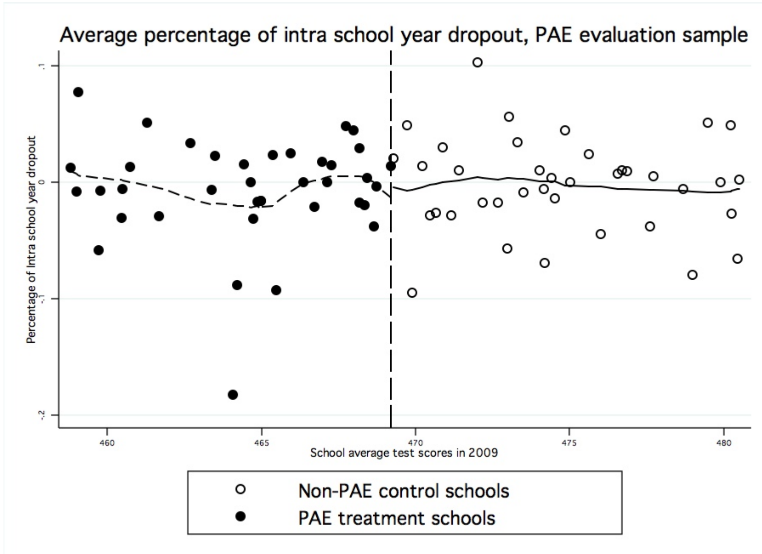

Figure 3.5: Dropout and average performance in 2009. Source:Author's calculation using 911

Figure 3.6 illustrates that student-to-teacher ratios are equal between PAE and non-PAE schools. The lack of discontinuity close to the cut-off indicates that these schools were equivalent with respect to this school input.

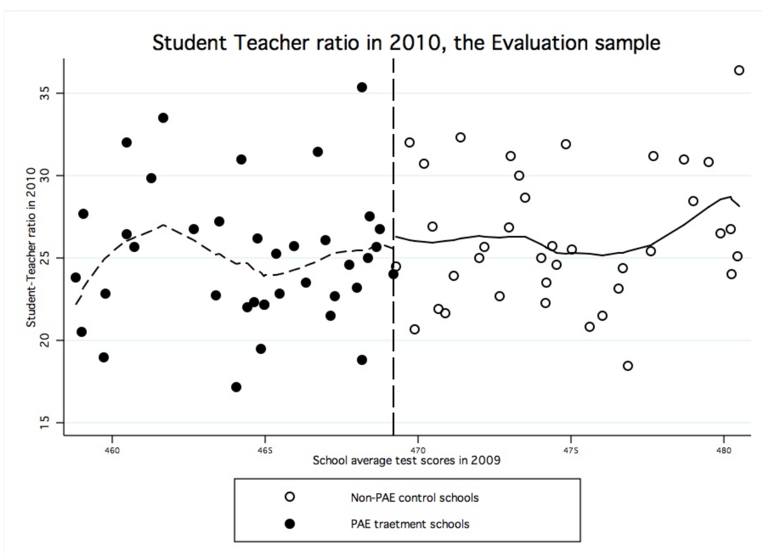

Figure 3.6: Student Teacher Ration. Source:Author's calculation using 911

Identification

As noted above, a simple approach to evaluating the PAE program would involve just a straightforward comparison of the differences in mean value of the outcome variable (e.g., test scores) between the PAE schools and non-PAE schools over time. Figure 3.7 illustrates this simple approach—without controls—using the full sample of the PAE and non-PAE schools, with a red line representing the 2009 baseline year (before the program). That is, Figure 3.7 depicts the overall mean test performance between PAE and non-PAE schools over seven years. In 2006, non-PAE schools out-performed PAE schools by about 0.40 s.d., and this gap increased in 2007. Between 2007 and 2009, both mean test scores decreased, but PAE schools decreased more. After 2009, both groups experienced an increase in their average test scores while still maintaining a difference in means similar to that of 2006. In short, it would appear the PAE program had no effect on test scores.

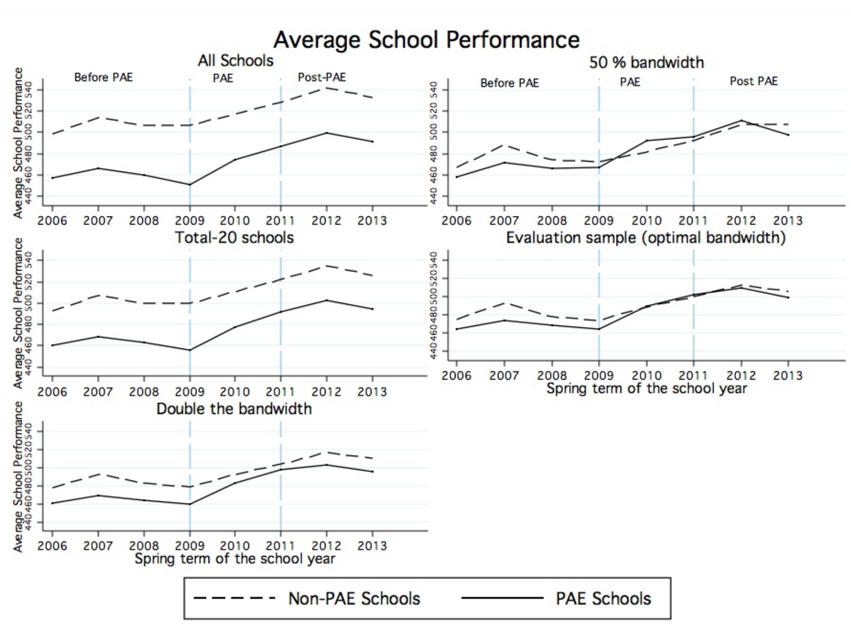

Figure 3.7: School Performance over time. Source:Author's calculation using ENLACE

As we shall see, Figure 3.7 depicts how a simple comparison might misrepresent the impact of the PAE program: PAE schools—before and after the program—underperform in comparison with the non-PAE schools and there does not appear to be any change after the program was implemented. The next step is to adopt the regression discontinuity design.

First, Figure 3.8 examines whether the assignment rule used in the selection of the poorest performing schools had actually been followed. That is, the graph shows the relationship between the average school achievement scores that were used to determine which schools were eligible for PAE and the percentage of those schools that actually received PAE information. Graph 3.8 shows that this rule was indeed followed: Every school that was eligible for PAE joined the program. So, the fact that the average school achievement score in 2009 was a deterministic forcing variable classifying PAE-treatment and non-PAE-control schools means that a sharp regression discontinuity methodology can be used to analyze the impact of the program.

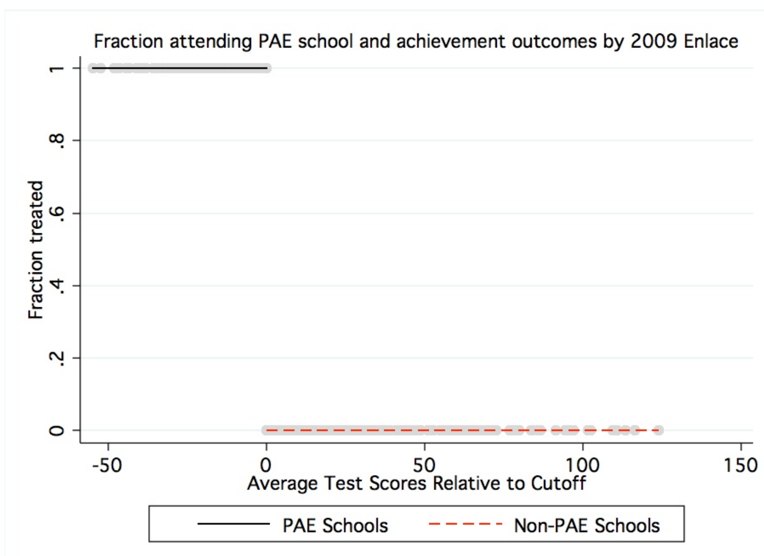

Figure 3.8: First Stage. Source:Author's calculation using ENLACE

Taking advantage of the quasi-experimental design resulting from a sorting of schools due to a specific test score cut-off, the analysis uses schools close to the cut-off point so that a valid comparison among similar groups can be constructed. Schools were arrayed on a forcing variable defined by their average test scores on the ENLACE achievement test and classified at an exogenous perfor-

Table 3.5: Evolution of Average Math Score in Colima based on ENLACE , Sample Evaluation

Year	NonPAE	PAE	Diff	S.E.
2006	476	464	11	(5.76)**
2007	492	473	19	(5.32)***
2008	481	468	12	(4.76)***
2009	475	464	11	(1.08)***
2010	489	490	-1	(6.15)
2011	502	501	1	(5.86)
2012	514	510	4	(5.88)
2013	508	499	9	(6.62)

Source: Author's calculations using ENLACE

mance cut-off point defined of 469.2. Schools with scores below the cut-off point were classified as PAE schools and schools with scores greater than the cut-off point did not receive the program. Table 3.5 shows the distribution of average math scores in Colima for the evaluation sample.

Using the sample of schools close to the cut-off, Figure 3.9 shows the distribution of average test scores by PAE-treatment and non-PAE treatment, including the overall sample of schools as well as the samples used for the regression discontinuity analysis, including the 50% bandwidth as well as the optimal bandwidth and double this bandwidth, as discussed earlier. The results for the overall sample of schools was just discussed, but comparing those results with those in the evaluation samples (close to the cut-off point) show significant differences. For all bandwidths used in the regression discontinuity design, the PAE schools tend to catch-up with the non-PAE schools after the implementation of the program. The suggestion is that the PAE program was indeed successful in raising student achievement, when similar schools are compared with each other.

Figure 3.9 focuses on the comparison of test scores between PAE and non-PAE schools before and after the PAE implementation threshold, using the optimal bandwidth. As it was discussed earlier, because of mean reversion between control and treatment schools or other factors, the use of rankings may lead to misclassification of schools across the treatment and control groups, but figure 3.9 shows the average school performance three years before the baseline and there is no significant difference in results, suggesting the absence of this type of problem.

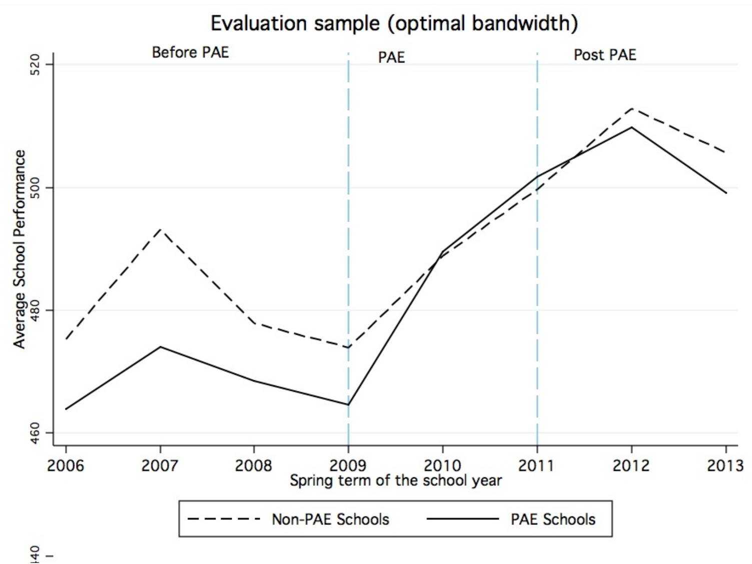

Figure 3.9: PAE sample. Source:Author's calculation using ENLACE

The descriptive picture provided by the diagrams in this section suggests that using a regression discontinuity method the PAE program may indeed have worked in raising student achievement. However, determining the exact impact requires estimating the production function equation specified above. This is discussed in the next section. For most of the statistical analysis reported below, the focus will be on the data that includes 66 schools on ($\pm$9.48) point around the cut-off, to ensure the statistical power and precision of the estimates, but the analysis was carried out with other bandwidths as well.

3.5 Results

Overall, the empirical results in this section suggest that the OLS "naive" estimates do not accurately reveal the causal relationship between the PAE intervention and average school performance.

Using the OLS approach, there appears to be a negative relationship: Schools subject to PAE did not improve on the basis of this intervention. But because this statistical approach may be subject to the presence of omitted variables, there may be a downward bias on the OLS estimate for the PAE impact on scores. This is investigated next, by using the regression discontinuity approach.

3.5.1 Differences in Differences at the school level results

Table 3.6 presents the effect of the PAE program on the average school test scores across bandwidths and time. In general, the estimates show that the relationship between the PAE program and school achievement is positive by 13.82 points of ENLACE (0.14 s.d.) with the preferred bandwidth ($\pm$9.48).

Different specifications, with various controls and different bandwidths, were used. The coefficients were all positive, and significant at the 95 level. That is, the PAE program increased ENLACE test scores by around 0.13 s.d. for a bandwidth of 38 schools on each side of the cut-off, and the estimate was significant at a 95% (p< .05) level of confidence. In particular, from the 2008-2009 school year to the 2009-2010 school year, average scores increased in all of Colima's schools. But they increased more in the PAE schools so that the 2010 the difference in differences estimates show a significant gain favoring the PAE over the non-PAE schools by around 0.16 s.d. for the optimal bandwidth. This suggests that the program had a positive impact on student achievement and that program helped reduce the gap that existed before the PAE was implemented between the PAE and non-PAE schools. [7].

[7] Two models where performed to estimate these effects: $Y_{s,t} = \alpha + \beta PAE_{s,t} + \gamma DuringPAE_s + \tau PostPAE_s + \delta Year \varepsilon_{s,t}$ and $Y_{s,t} = \alpha + \beta PAE_{s,t} * Year + \varepsilon_{s,t}$

Table 3.6: Effects of PAE on average learning achievement, Colima 2006-2013

	All	±18.97	±9.48	±4.74
PAE	9.92	13.02	13.82	12.60
	(3.628)***	(3.545)***	(4.89)***	(6.507)**
Observations	2452	964	528	304
PAE 2010	4.13	9.44	15.46	23.46
	(6.113)	(6.39)	(8.82)*	(11.74)**
Observations	2452	964	528	304

Source: Author's calculations using ENLACE (2006-213)
*** 99% ** 95% *90% . Full results in the annex.

3.5.2 Second stage, graphical analysis

Figure 3.10 illustrates the reduced form relationship between average school performance in 2010 (vertical axis) and the performance in 2009 relative to the cutoff test score (horizontal axis). The PAE schools are to the left of the cut-off, which was of course used for their eligibility into the program, and the non-PAE schools are to the right. A clear discontinuity appears at the normalized cut-off (zero): there is a general pattern showing that schools on the left of the cut-off (the PAE schools) display greater gains in tests scores in 2010 than those schools on the right of the cut-off (the non-PAE schools). This graphic illustration suggests that the PAE program did, after all, have an effect on school outcomes. This short-run impact of the program may be attributable to the information and analysis that the accountability component of the PAE program provided to the PAE schools about their educational status and the problems their students encountered.

School Average Performance 2010, PAE vs Non-PAE, Impact Evaluation Sample

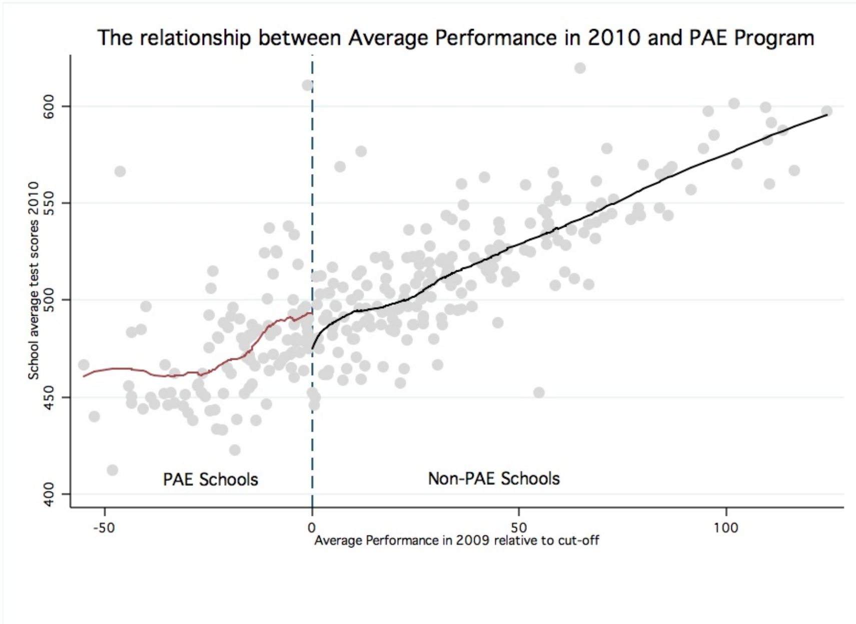

Figure 3.10: Second Stage, 2010.

Analyzing the impact of the program after one year, when the schools may have implemented some pedagogical interventions (because the program ended, they were not provided with any additional resources as part of the program itself) provides additional information on the impact of the PAE. This second stage of the analysis, examining test scores for 2011, reveals a small discontinuity at the cut-off. Schools on the left of the threshold have an average achievement in 2011 slightly higher than those schools on the right of the cut-off.

School Average Performance 2011, PAE vs Non-PAE, Impact Evaluation Sample

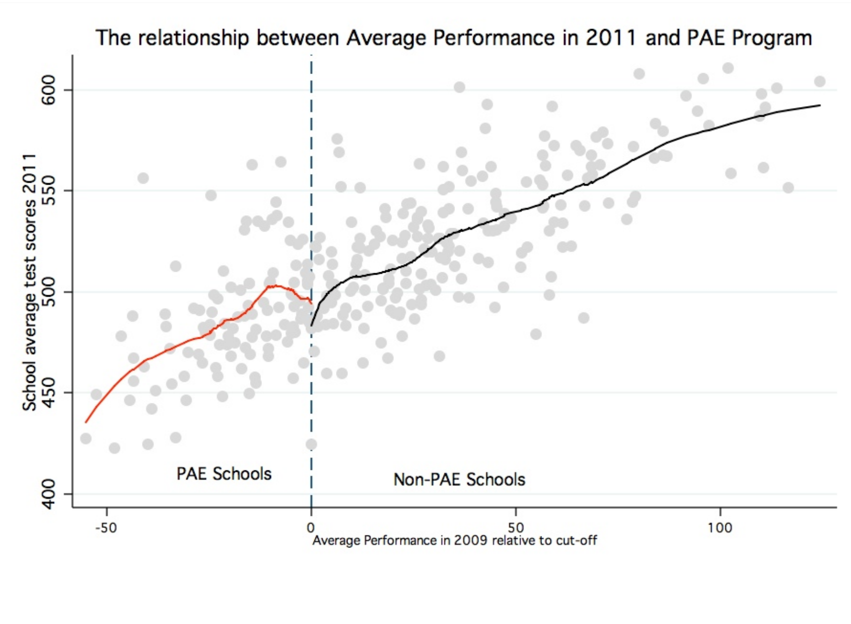

Figure 3.11: Second Stage, 2011.

By 2012, two years after the implementation of the program, the relationship between average school performance and the forcing variable has dissipated. No achievement differences arise at the cut-off.

School Average Performance 2012, PAE vs Non-PAE, Impact Evaluation Sample

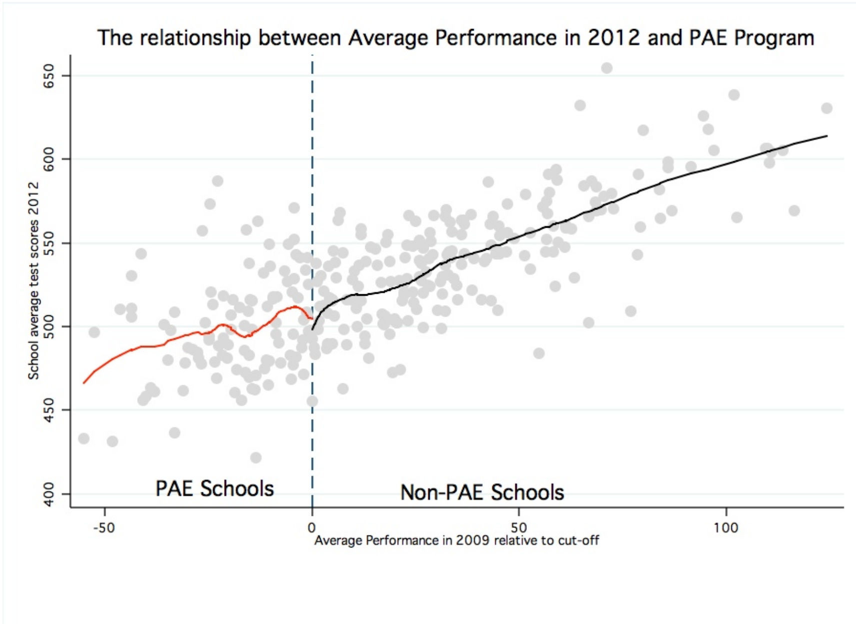

Figure 3.12: Second Stage, 2012.

3.5.3 Second Stage, Econometric results

This section extends the graphical analysis in the last section by discussing the results of the PAE program over time using the coefficients of the estimated equations. Recall that the PAE program consisted of two components: accountability intervention then followed by pedagogical intervention. If the first component impacted test scores, the effect would presumably (though not necessarily) be observed before the implementation of the second component. As evidenced in Table 3.7, the relationship between schools subject to PAE accountability intervention and average test scores suggests that the PAE program had an effect on school outcomes.

Figure 3.13 illustrates the impact of the program comparing schools around the cutoff. The significant of these coefficients relies on the clustered S.E. at the school level.

Table 3.7: Effects of PAE on average learning achievement, Colima 2010

Model	Sample	Coefficient	S.E.
±18.97	13516	19.41	(13.35)
±9.4	7424	44.32**	(20.90)
±4.74	13494	99.92**	(47.66)

Each model includes controls.
All regressions are clustered by schools
*** 99% ** 95% *90%

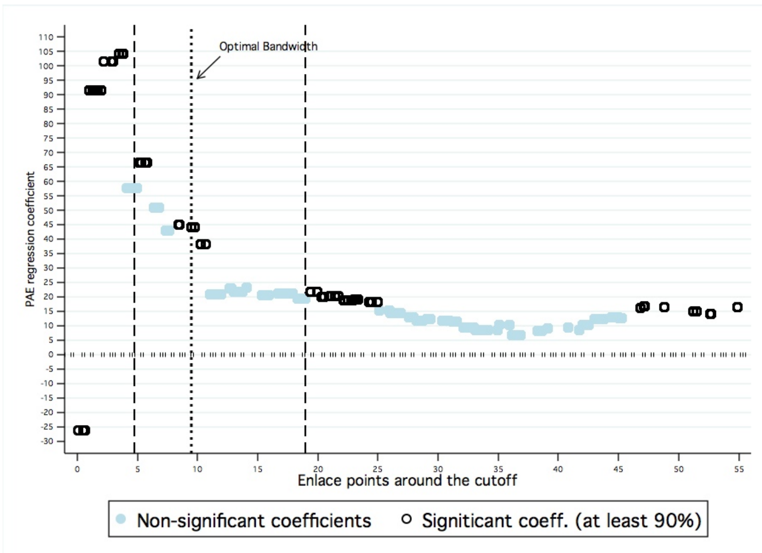

Figure 3.13: Second Stage, 2010, Impact Evaluation Sample. Source:Author's calculation using ENLACE

While the results show a positive 0.42 s.d. impact on the average school scores for the preferred bandwidth, it is possible that the PAE program impacted scores on a subject-by-subject basis. Table 3.8 shows the estimates for math, Spanish (reading) and other (subjects tested changed very year and they were, therefore, rotative). Indeed, the effect of the program was consistent across subjects. The program had a positive effect of 0.41 in Spanish (for the optimal bandwidth). In Math, PAE schools were impacted by an average of 46 points (with a statistical significance of 95 % ($p < .05$). The PAE intervention also had an impact on rotative subject performance for schools.

After only one year and half (school year 2011-2012), the PAE program was discontinued. Using data from 2011, the results indicate that the PAE program had no longer a significant impact in increasing average test scores. For 2012, an analysis does not detect either a significant effect on test

Table 3.8: Effects of PAE on average learning achievement, Colima 2010

Model	Sample	Coefficient	S.E.
±9.4 Math	7333	46.51**	(21.42)
±9.4 Spanish	7304	41.20**	(20.10)
±9.4 Rotative	7356	44.46*	(24.17)

Each model includes controls.
All regressions are clustered by schools
*** 99% ** 95% *90%

score gains, and the results are consistent across specifications. So, although there was a short-run gain in test scores, the test scores stopped rising after two years.

3.5.4 Threats to Internal Validity

As is the case with all regression discontinuity designs, threats to internal validity need to be investigated and, if possible, mitigated. Tests for discontinuities in covariates unrelated to the treatment at the cut-off point, and tests for discrepancies at non-discontinuity points must be conducted. Additionally, other weaknesses can be avoided by ensuring that sufficient observations around the cut-off point exist and that the analysis is generalizable to the entire population. As previously mentioned, the PAE cut-off point was entirely determined by the government (presumably by budget considerations), making it exogenous. Second, as detailed above, the Colima education data bases include rich data on students in all schools; this ensures that the number of observations around the cut-off point is sufficient to support statistical inferences. Finally, since the PAE is a special program intended to target a special population, the fact that its results may be valid only for a specific population subgroup is not a point of concern; we are interested in the impact PAE had on these lower-performing schools.

As for unrelated covariation, Table 3.9 shows the regression discontinuity estimates of the effect of the intervention given average student-to-teacher ratios. The results are not significant, suggesting that schools were similar with respect to this covariate.

Table 3.9: Effects of PAE on average Student-Teacher Ratio, Colima 2010

Model	Sample	Coefficient	S.E.
28 ES	6160	-3.92e-16	(1.19e-15)
25 ES	5566	7.34e-16	(1.27e-15)
20 ES	4482	-2.59e-16	(7.24e-16)

Each model includes controls.
All regressions are clustered by schools
*** 99% ** 95% *90%

By the same token, Table 3.10 shows the regression discontinuity estimates of the effect of the intervention given average marginality rates. Again, the results are not significant.

Table 3.10: Effects of PAE on average marginality, Colima 2010

Model	Sample	Coefficient	S.E.
28 ES	6160	.16	(.136)
25 ES	5566	.22	(.135)
20 ES	4482	.23	(.144)

Each model includes controls.
All regressions are clustered by schools
*** 99% ** 95% *90%

What about schools artificially manipulating their test scores, which is often done by the appalling practice of excluding low-performing students from taking the exam? (Reback and Cullen, 2006; Figlio and Getzler, 2002; Jacob and Levitt, 2003). Table 3.20 in the Annex lists the average number of students who did not participate in ENLACE 2009, 2010 and 2011 in PAE-treated and non-PAE-control schools. The average number of missing students was similar across all groups and times. There is, then, at least no evidence of systematic exclusions.

Given that all these results have been reported in aggregate, they do not reflect the possible heterogeneous effects of treatment. Table 3.18 illustrates the impact of the program across the distribution and cut-off. Using a quantile regression, the impact of the program for the preferred bandwidth are only significant at bottom 10% with a coefficient of 9.5 and the last three deciles by12.41,18.6, 19(70% and 80% and 90%). This result suggests that the program did not have an impact for the average student. In addition, Table 3.19 details the various activities and practices of principals of PAE and non-PAE schools in 2010. The Table shows the mean differences across Principal's task, where PAE principals had better indicators in terms of accountability and management capacity. That is, a potential mechanism of PAE improvement was the change of school management of the Principal in PAE schools.

3.6 Discussion

In 2010, the state of Colima established an accountability strategy and identified 108 schools that had obtained the lowest learning outcomes as measured by ENLACE. In early February 2010, the state governor announced the "performance status" of selected schools: Schools which performed below an arbitrary cut-off were automatically enrolled in a mandatory *Programa de Atención Específica para la Mejora del Logro Educativo* (PAE). The program, however, was ended in the 2011-2012 school year.

By exploiting PAE's eligibility rules, a sharp regression discontinuity was used to estimate the impact on subsequent learning outcomes. Schools that participated in the program and a valid comparison group were followed for three years in order to compare their performance. The results of a statistical analysis of this natural experiment confirm the positive effect of the PAE program on average test scores in poorly performing schools in the Mexican state of Colima. There are many potential explanations of this impact. First, principals and teachers may have focused on teaching to the test. Curriculum and ENLACE are linked by design and ENLACE was used to show the weakness areas in the classrooms of the low-performing schools. It is possible that teachers used this information to teach the subjects that were more closely connected to the test. Second, the pressure put on teachers by being declared low-performing schools may have created incentives to practice some type of cheating. ENLACE uses two algorithms to detect cheating and results are invalidated when it happens. There is no evidence of test scores invalidation by the Ministry of Education of Colima to any PAE schools (under the preferred bandwidth). In addition, the percentage of students who did not take ENLACE during the intervention was equal than non-PAE schools, which suggests the PAE schools did not try to manipulate test scores by choosing the students who took the test Third, student mobility across schools might have affected the test scores after the PAE schools were identified. But such mobility is very difficult without a reason other than geographic reallocation of student's family. In addition, it would have been more likely that the best students would have moved out of PAE schools, which –if anything—it would suggest the impact of the program could have been stronger than suggested by this study.. Fourth, another plausible explanation is that the intervention may have changed the expectations of the school actors. That is, teachers may have increased effort due to future expectations of punishment. While expectations are a consistent story, it goes in the same direction than the accountability story that this analysis supports. Therefore, the results of a statistical analysis of this "natural experiment" confirm that the accountability intervention embodied by the PAE program had a positive impact on average test scores in poorly performing schools in the Mexican state of Colima. In the short-term, the PAE schools responded to feedback information by improving the quality of the education they provided. The size of the three-year effects align with studies that evaluate the impact of accountability measures on test scores, with values ranging from 12% to 15% s.d. on performance outcomes.

The fact that the PAE program was halted after only one year suggests that the main intervention of the program was circumscribed to the detailed information provided to the schools about the test scores of their students, the activities connected to the preparation of a program of change at the school level, and any pedagogical reforms induced by these activities. Activities during the period of preparation revolved started by notifying schools they were low-performing, identifying the school's main academic problems and devising a development plan to address those challenges. Thus, if the PAE program were to have an effect on test scores, the mechanism of influence would be limited simply to school notification, problem identification and reform conceptualization. Yet after only one year, test scores in PAE schools increased by 0.4 s.d. vis-à-vis non-PAE schools and differences between these two groups were not significant for the three years of the experiment. As Koning and van der Wiel (2013) observes (from a study in the Netherlands), "naming and shaming" can itself effectuate change.

The results of this chapter indicate that full and wide dissemination of information detailing school quality is critically important. When students, teachers and parents in a school know that their scores are low, and this triggers a process of self-evaluation and analysis, the process itself may lead to an improvement in learning outcomes. There may also be a motivational impact connected to the ranking of a school relative to others, linked to the "naming and shaming" social pressure that arises from being labeled a low-performing school.

According to this analysis, it is not so much the inputs made available by an intervention program, but the signaling value of the program, the associated diagnosis and networking opportunities with other school officials and advisers which result in school improvements. Moreover, unlike the high-stakes consequences for schools in the United States, or the sacking of officials in England, or the lead with your feet school choice in the Netherlands, the policy (or at least de facto events) in Colima bore no punitive actions against school actors.

So while the PAE program in Colima was surprisingly and frustratingly short-lived, it's premature termination serves to highlight a largely unrecognized phenomenon: acknowledgment is, in some ways, virtually tantamount to improvement. After all, if you really understand the problem, effective solutions come much easier. If you don't understand the problem, no amount of "problem-solving" can be expected to work. This is why future research must focus on documenting how school administrators, teachers, parents and students interpret, internalize and react to indications that their school is underperforming.

One may still legitimately wonder why schools did not improve before the PAE program given that the same information was already disclosed publicly. Perhaps the information was not well understood or disseminated, or beleaguered school leaders in poorly performing schools could not—without the right logistical support and networking—begin to proactively respond to more, and as it were, even louder, bad news. These are all areas of future research. Moreover, a federal Mexican program similar in nature to PAE—the Program to Improve Academic Achievement (PEMLE)—could no doubt benefit from more research in this vein. It remains refreshing, however, that quality information, without punitive measures but within a supportive and collaborative environment, appears to be sufficient for improved learning, as demonstrated in this chapter.

3.6.1 Tables and Figures

School Average Performance 2010, PAE vs Non-PAE, Impact Evaluation Sample

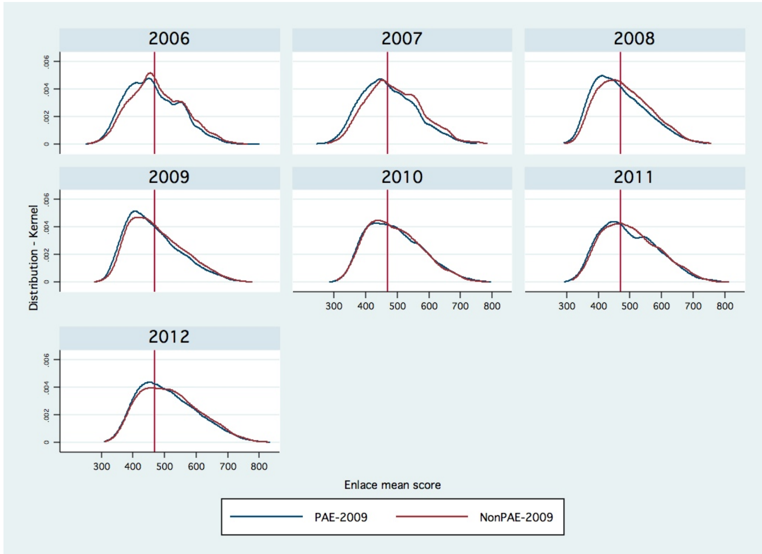

Figure 3.14: Density of School Average Performance, PAE vs Non-PAE

Table 3.11: Differences and Differences -PAE results

	(All)		76		33		28		25	
	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.
PAE School	-56.53***	(1.880)	-16.12***	(2.172)	-15.36***	(2.111)	-14.23***	(2.418)	-14.10***	(2.557)
During PAE	9.92***	(3.628)	13.02**	(3.545)	13.82**	(4.89)	12.60**	(6.507)	11.03**	(5.049)
After PAE	0.166	(5.790)	-2.8	(7.761)	-3.31	(8.250)	-2.874	(10.14)	-5.845	(10.46)
2007	13.30***	(3.633)	11.10**	(3.767)	12.11***	(3.641)	11.67**	(4.240)	13.44**	(4.468)
2008	4.405	(3.449)	6.043	(3.572)	6.266	(3.260)	4.72	(3.789)	5.43	(3.892)
2009	3.539	(3.510)	0.0491	(2.963)	0.913	(2.692)	-0.7	(3.188)	1.321	(3.266)
2010	16.24***	(3.909)	17.10***	(4.417)	18.15***	(4.340)	17.84***	(5.145)	21.39***	(5.438)
2011	27.12***	(3.815)	24.66***	(4.368)	24.00***	(4.146)	23.07***	(4.878)	26.35***	(5.049)
2012	40.40***	(3.900)	37.58***	(4.502)	37.14***	(4.351)	37.09***	(5.214)	39.61***	(5.443)
2013	32.10***	(4.318)	33.20***	(5.247)	34.10***	(5.469)	33.96***	(6.769)	38.01***	(7.061)
Constant	510.1***	(2.697)	477.8***	(3.312)	476.4***	(2.897)	477.5***	(3.404)	475.4***	(3.571)
Observations	2452		606		526		448		408	

*** 99% ** 95% *90%

PEMLE versus PAE

What is the target population? What are the characteristics defining the target population benefiting from this program?

PEMLE : 29,147 primary (grades 1-6) and lower secondary (grades 7-9) schools in which 50 percent or more of the students obtained an “insufficient” level on the 2009 ENLACE exam. The program divides the 29,147 schools into 3 categories: Category 3: 29,147 schools in which 50

Table 3.12: Differences and Differences estimation of PAE impact

	(All)		±18.97		±9.48		±4.74	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
PAE School	-50.95***	(3.910)	-18.75***	(4.371)	-14.88**	(5.309)	-19.25**	(6.058)
2007	14.80**	(4.553)	13.21**	(4.244)	14.11*	(5.476)	11.37	(8.092)
2008	5.447	(4.335)	7.082	(4.168)	6.177	(5.049)	8.786	(6.914)
2009	5.773	(4.422)	-1.228	(3.482)	-2.274	(4.117)	-2.843	(5.112)
2010	17.73***	(4.531)	14.76***	(3.988)	15.87**	(5.106)	15.21*	(7.314)
2011	28.53***	(4.429)	24.84***	(4.186)	23.18***	(5.206)	25.06***	(7.238)
2012	41.13***	(4.516)	39.13***	(4.810)	38.83***	(5.502)	34.40***	(6.822)
2013	33.30***	(4.641)	31.30***	(5.315)	33.43***	(6.302)	36.18***	(8.626)
PAE 2007	-6.987	(5.594)	-7.490	(5.720)	-4.792	(7.252)	6.309	(9.247)
PAE 2008	-4.865	(5.333)	-5.697	(5.758)	-0.324	(6.662)	3.601	(8.267)
PAE 2009	-10.32*	(5.191)	0.740	(4.584)	5.300	(5.424)	14.48*	(6.140)
PAE 2010	4.131	(6.113)	9.449	(6.397)	15.46	(8.829)	23.46*	(11.75)
PAE 2011	4.554	(5.651)	10.24	(5.944)	12.14	(7.549)	14.17	(8.712)
PAE 2012	7.577	(6.215)	7.339	(6.799)	6.781	(7.901)	15.78	(8.839)
PAE 2013	5.665	(6.472)	9.046	(7.378)	8.349	(9.185)	6.866	(10.82)
Constant	508.9***	(3.185)	479.8***	(3.355)	476.6***	(4.054)	474.8***	(5.038)
Observations	2452		964		528		304	

*** 99% ** 95% *90%

Table 3.13: RD- 2010 -PAE results by subject- with controls and grade and cluster correction of the SE

	Spanish		Math		Other	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
PAE	41.20**	(20.11)	46.51**	(21.42)	44.47*	(24.17)
Forcing Variable	502.4	(474.3)	1076.3*	(478.2)	732.3	(447.3)
FV^2	-0.527	(0.499)	-1.134*	(0.504)	-0.770	(0.471)
$PAE*(FV-cutoff)$	1.600	(6.901)	-2.614	(8.415)	-1.732	(8.897)
$(PAE*(FV-cutoff))^2$	1.380	(0.747)	1.986*	(0.856)	1.576	(0.934)
Low Marginality	-19.91*	(7.673)	-24.13**	(9.032)	-13.64	(10.44)
Medium Marginality	1.158	(5.884)	2.020	(5.692)	2.707	(6.383)
High Marginality	5.567	(10.41)	16.50	(13.30)	34.51*	(15.58)
Carrera Magisteria	-8.870	(8.933)	-13.26	(9.020)	-8.172	(8.935)
Student/Teacher	1.785	(0.991)	2.356*	(1.075)	1.974	(1.268)
Teachers with HE	47.79**	(14.94)	38.73	(19.83)	37.51*	(15.39)
Grade 4	-33.04***	(4.519)	-18.47**	(5.466)	9.290	(5.849)
Grade 5	-43.48***	(5.427)	-37.63***	(6.298)	2.790	(5.506)
Grade 6	-17.72**	(5.796)	-6.466	(6.559)	-6.535	(5.935)
Constant	-119164.7	(112632.6)	-254969.7*	(113485.5)	-173759.0	(106155.7)
Observations	7304		7333		7356	

*** 99% ** 95% *90%

percent of the students obtained an insufficient level in the 2009 ENLACE exam, but not consecutively in the 2007 ENLACE and 2008 ENLACE exams.

Category 2: 9,882 schools in which 50 percent of the students obtained an “insufficient” level in the ENLACE exams since 2007 until 2009 are not situated in poor areas.

Category 1: 7,395 (of the 9,882 schools in Category 2) in which 50 percent of the students obtained an “insufficient” level in the ENLACE exam since 2007 until 2009 and are situated in school zones in which at least three schools fulfill the condition of poor areas. This program is a national program.

Table 3.14: RD- 2011 -PAE results- with controls and cluster correction of the SE

	±4.74		±9.48		±18.97	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
PAE	101.0**	(50.42)	41.05**	(21.36)	16.56	(13.10)
Forcing Variable	6656.8	(4071.0)	699.6	(408.6)	90.64	(89.03)
FV^2	-7.054	(4.314)	-0.736	(0.430)	-0.0937	(0.0928)
$PAE*(FV-cutoff)$	-0.267	(33.89)	0.279	(8.070)	-2.359	(3.563)
$(PAE*(FV-cutoff))^2$	12.85	(6.380)	1.583	(0.800)	0.0131	(0.186)
Low Marginality	-52.24	(31.45)	-16.84*	(7.699)	-12.19**	(3.717)
Medium Marginality	-2.624	(6.694)	5.628	(5.439)	-0.702	(3.981)
High Marginality	3.732	(17.87)	22.38	(14.13)	12.51	(13.05)
Carrera Magisteria	-24.83	(15.60)	-12.66	(11.65)	-5.413	(7.962)
Student/Teacher	3.434*	(1.591)	1.697	(0.877)	1.050	(0.601)
Teachers with HE	19.25	(27.24)	45.42*	(21.80)	35.54**	(12.51)
Constant	-1570049.1	(960385.2)	-165859.3	(97015.2)	-21457.1	(21352.6)
Observations	4173		7432		13516	

*** 99% ** 95% *90%

Table 3.15: RD- 2010, PAE results- with controls and grade and cluster correction of the SE

	±4.74		±9.48		±18.97	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
PAE	99.92**	(47.67)	44.33**	(20.91)	19.42	(13.35)
Forcing Variable	45.57	(30.12)	9.635	(5.163)	3.004	(1.964)
FV^2	-8.603	(5.602)	-0.774	(0.442)	-0.109	(0.0909)
$PAE*(FV-cutoff)$	13.44	(6.679)	1.650*	(0.774)	0.0516	(0.193)
$(PAE*(FV-cutoff))^2$	-16.26	(39.09)	-0.239	(7.254)	-2.230	(3.668)
Low Marginality	-40.34	(23.43)	-19.45*	(8.295)	-12.31**	(4.299)
Medium Marginality	-6.051	(7.188)	1.978	(5.177)	-2.138	(3.463)
High Marginality	-1.311	(13.69)	19.26	(12.32)	10.88	(12.50)
Carrera Magisteria	-7.244	(11.23)	-10.24	(8.173)	2.245	(6.001)
Student/Teacher	4.076*	(1.714)	2.005	(1.062)	0.709	(0.484)
Teachers with HE	24.02	(18.67)	41.50**	(15.00)	24.62*	(10.64)
Grade 4	-18.05**	(5.804)	-14.10**	(4.627)	-20.02***	(3.781)
Grade 5	-34.70***	(5.547)	-25.87***	(4.995)	-25.38***	(3.342)
Grade 6	-15.16*	(7.006)	-10.03	(5.596)	-11.34**	(3.775)
Constant	348.0***	(59.39)	420.5***	(29.41)	468.0***	(14.39)
Observations	4169		7424		13494	

*** 99% ** 95% *90%

Table 3.16: RD- 2011 - Simplest model of PAE results- with controls and grade and cluster correction of the SE

	(1)		(2)		(3)		(4)	
	All		38 ES		33 ES		28 ES	
PAE	5.234	(3.201)	6.265	(7.542)	-0.0256	(9.231)	4.410	(9.947)
Forcing Variable	0.791***	(0.0404)	2.115**	(0.707)	1.486	(0.922)	1.831	(1.711)
$PAE*(FV-cutoff)$	0.0218	(0.134)	-2.399*	(1.157)	-2.285	(1.712)	-2.229	(2.432)
Low Marginality	-5.122	(3.055)	-9.991	(5.742)	-7.256	(6.302)	-5.675	(8.992)
Medium Marginality	0.325	(2.352)	-11.20*	(4.523)	-11.87*	(4.892)	-13.24*	(5.511)
High Marginality	-0.452	(4.264)	-5.939	(8.685)	-0.0573	(10.55)	-10.90	(8.982)
Carrera Magisterial	9.984**	(3.349)	16.41*	(6.498)	16.11*	(7.203)	7.819	(7.983)
Student/Teacher	0.461*	(0.218)	-0.563	(0.596)	-0.898	(0.690)	0.112	(0.628)
Teachers with HE	6.041	(5.505)	-6.004	(10.19)	-6.086	(10.43)	13.31	(11.71)
4th Grade	-6.653*	(2.598)	-2.675	(4.861)	-2.994	(5.362)	-2.953	(6.233)
5th Grade	-9.063***	(2.438)	-1.673	(4.365)	-0.618	(4.746)	-3.402	(5.316)
6th Grade	-2.534	(2.616)	-1.504	(5.743)	-0.589	(6.361)	-5.868	(6.225)
Constant	114.4***	(19.93)	-483.8	(332.0)	-177.5	(434.3)	-365.2	(808.9)
Observations	39832		8871		7807		6330	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.17: RD- 2012 - Simplest model of PAE results- with controls and grade and cluster correction of the SE

	(1)		(2)		(3)		(4)	
	All		38 ES		33 ES		28 ES	
PAE	3.925	(3.451)	8.943	(7.040)	7.931	(7.973)	1.045	(9.871)
Forcing Variable	0.862***	(0.0402)	1.716*	(0.691)	1.695	(0.994)	2.922	(1.616)
$PAE*(FV-cutoff)$	-0.353*	(0.153)	-2.018	(1.083)	-1.845	(1.396)	-8.111**	(2.519)
Low Marginality	-0.345	(3.208)	-1.762	(6.115)	-0.920	(6.757)	3.737	(8.859)
Medium Marginality	4.827*	(2.387)	3.943	(4.414)	3.064	(4.826)	-0.589	(5.084)
High Marginality	-5.453	(4.287)	-18.64**	(6.545)	-16.02*	(7.229)	-24.96**	(7.923)
Carrera Magisterial	10.70**	(3.660)	28.82***	(6.672)	28.03***	(7.130)	22.88**	(8.414)
Student/Teacher	0.442*	(0.224)	0.146	(0.492)	-0.0701	(0.546)	1.129	(0.728)
Teachers with HE	6.986	(5.671)	-5.091	(8.890)	-6.596	(9.281)	-2.011	(11.20)
4th Grade	3.583	(2.545)	-3.656	(4.853)	-2.515	(5.237)	-0.441	(5.971)
5th Grade	-3.543	(2.538)	-10.35*	(5.067)	-10.81	(5.535)	-10.59	(6.062)
6th Grade	2.064	(2.691)	-0.0888	(5.337)	0.475	(5.786)	-0.142	(6.305)
Constant	84.93***	(20.06)	-313.1	(324.4)	-296.4	(468.6)	-904.9	(765.6)
Observations	43429		9771		8583		7000	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

PAE: 110 primary schools which obtained lower educational scores based on the ENLACE scores of the students. This program is specific to the state of Colima.

What is the treatment of the program?

PEMLE: The program offers three specific attention packages (PAE Paquete de Atención Específica) designed to suit the needs of schools each category. The schools in category 3 receive PAE 3, the schools in category 2 receive PAEs 2 and 3, and the schools in category 1 receive all of the PAEs.

PAE: The program consists of three phases. The first phase is a diagnostic phase in which schools are chosen, prepared to receive the program, and finally introduced to the program. This occurred during the 2010-2011 school year. The second phase is the strengthening of the program during the school years between 2011 and 2013. The third phase focuses on consolidating the PAE program in all 110 schools and seeing improvement in the academic achievements of the students during the school cycles between 2013 and 2015.

How long will the program last?

PEMLE: The program was designed between December 2009 and January 2010, gestated between January 2010 and March 2010, and implemented in schools starting March 2010 to the present day.

PAE: The program began during the 2009-2010 school cycle and will end with the 2015 school cycle.

How was the target population selected?

PEMLE: The selection of schools was initially organized under the national coordination of the PEMLE, and was later completed by the education authorities at the state level, who had the privilege of adding those schools they thought needed the help of the program.

PAE: The selected schools were a result of a budget restriction that only allowed for 110 primary schools to receive the program. These 110 scores where the schools receiving the lowest ENLACE scores.

What is expected of the program?

PEMLE: The program is expected to help those selected primary and lower secondary schools emerge.

PAE: Increase the percentage of students by 25% to higher scoring levels in the ENLACE exam.

Table 3.18: Regression Discontinuity Quantile Regression

	76 schools		66 schools		56 schools		310 schools	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
q1	9.4	(3.63)***	9.50	(3.89)***	7.17	(4.44)	12.78	(4.93)***
q2	4.7	(3.82)	2.56	(4.00)	4.67	(4.47)	14.01	(5.00)***
q3	2.6	(4.36)	6.77	(4.61)	8.83	(5.16)*	16.13	(5.51)***
q4	6.6	(4.71)	2.12	(5.10)	9.36	(5.65)*	18.37	(6.37)***
q5	2.4	(5.02)	2.42	(5.41)	9.42	(6.07)	19.93	(7.23)***
q6	5.1	(5.30)	5.73	(5.83)	13.69	(6.83)**	15.95	(8.05)**
q7	9.1	(5.72)	12.41	(6.36)**	28.72	(7.12)***	32.64	(8.07)***
q8	11.8	(5.73)**	18.66	(6.25)***	32.98	(7.42)***	41.10	(7.97)***
q9	18.5	(7.39)***	19.00	(7.66)***	41.36	(9.88)***	61.11	(11.00)***

Each model includes controls.
The original set of the evaluation sample (ES) is 38 schools.
All regressions are clustered by schools
*** 99% ** 95% *90%

Table 3.19: Differences across Principals' indicators, PAE vs Non-PAE

	Non-PAE	PAE	Diff	S.E.
How often do you evaluate teacher's attendance?	3.42	3.79	-0.37	0.02 *
How often do you evaluate teacher's puntuality?	3.45	3.73	-0.28	0.02 *
How often do you evaluate teacher's senority?	2.17	1.99	0.19	0.03 *
How often do you evaluate teacher's support to students?	2.69	3.09	-0.40	0.02 *
Do teachers receive monetary benefits for performance?	0.33	0.29	0.03	0.01 *
How often do teachers miss classes?	0.80	0.67	0.13	0.02 *
How often are teachers evaluate?	0.81	0.84	-0.04	0.02 *
How often do supervisors visit the school?	3.28	3.83	-0.55	0.03 *
How often do you visit the classrooms?	3.91	4.01	-0.10	0.02 *
How often do you evaluate teacher's performance?	2.34	2.40	-0.06	0.02 *
How often do you evaluate student's performance?	2.74	2.54	0.20	0.02 *
How often does the school give report cards to parents?	3.00	3.05	-0.05	0.00 *
How often do you discuss how to evaluate learning in meetings?	2.73	2.74	0.01	0.02
How often do you discuss how to improve learning?	2.85	2.82	0.03	0.02
Does the school use enlace to help low performance students?	0.95	0.90	0.03	0.07 *

Source: Principal Questionnaires
*** 99% ** 95% *90%

Table 3.20: Average number of students missing ENLACE evaluation sample

	2009		2010		2011	
	PAE	Non-PAE	PAE	Non-PAE	PAE	Non-PAE
3th	2	0	5	3	9	7
4th	9	10	1	-1	5	3
5th	2	-4	6	8	2	-2
6th	-4	-6	1	-4	5	7

Source: ENLACE.*** 99% ** 95%

Chapter 4

The Impact of Delaying Formal Schooling and the Effect of School-Entry Age on Student Achievement in México.

4.1 Introduction

Early childhood development (ECD) research has received growing attention in recent years due to the potential benefits for investments during this period. According to a review of ECD programs conducted by Currie (2001), the evidence demonstrates that ECD programs have short-term, medium-term and long-term benefits, and in particular, for disadvantaged populations. While the ECD period involves biological and cognitive processes which interact with chronological and environmental factors (social, culture, physical, etc.), it is not clear exactly when interventions must be timed in order to provide the highest returns. On the one hand, chronological age is an important parameter used to time investments during the ECD period. Cahan and Cohen (1989) mention that "chronological age actually stands for both biological and psycho-educational development" (p. 1239). On the other hand, the timing of formal schooling—a major cognitive investment—must also be carefully evaluated in order to achieve the greatest return on this expensive and complex socially administered intervention. This is why one of the principal debates in early childhood development is the age formal education should start.

Nowadays, there is no discussion regarding whether or not children should attend school. The debate now centers on the best timing for children to begin formal academic instruction. Parents, schools, governments and society at large must decide when children should begin going to school. Ideally, in order to promote equality and inclusion, governments should allow children to attend school without restriction. In reality, however, education systems inevitably attempt to "optimize" this timing by using more or less arbitrary cut-offs.

Entry-age laws differ from country to country. According to the UNESCO database, in 2013, there were 25 countries whose primary school start age was five, a total of 137 countries whose entry age was six, and 41 countries for which it was 7. Even within the same country entry-age practices are subject to change. Identifying the best age to start formal education can maximize the efficiency of children's learning. However, age-setting can also distort a variety of other objectives children, parents and other school actors value. For example, Stipek (2002) observe that test scores can be increased virtually for free merely by increasing the minimum age of school admission. Of course, this policy unfairly postpones schooling for otherwise eligible students.

What, then, is known about the best time to start school? Is it merely a question of whether or not younger entrants gain more or less from schooling than older entrants? In economics, human capital theory focuses on how individuals aim to select an optimal cognitive achievement schedule, one which emphasizes high returns on early investments in the life cycle. In addition, human capital theory assumes that individuals optimize their life earnings so they will have more working life after they have completed their human capital accumulation (marginal benefit) and will incur lower forgone earnings (marginal cost) Berndt (1990). However, there is evidence that "readiness" is also an important factor in the learning process. Black et al. (2008) mention that "It is possible that children cannot learn as well in school earlier in their developmental life" (p. 213).

While the long-term effects of early entry are clearly and consistently positive, the short-term effects of early entry are not so obvious. According to Black et al. (2008), older students perform better in school. Moreover, students who start earlier out-perform those of the same age but who delayed their entry into school. To be sure, empirical evidence on this subject is inconclusive, and many questions regarding the "right" age to begin formal academic instruction remain unanswered for many reasons. First, the effect of school entry age has been studied by correlating age and the attainment of academic skills through various counterfactual hypotheses. Second, the research conducted so far has analyzed different empirical questions or manipulated different variables, undermining the interpretability or generalizability of the studies. Third, while most of the empirical evidence has used a "cut-off approach" to address the existence of omitted factors, the empirical designs vary widely. Finally and most importantly, the methodologies used—combined with the lack of a unified theory—inevitably confuse direct age effects with the indirect effects of age on learning. For example, Black et al. (2008) argue that "Most of the literature has compared test scores of children who are in the same grade and so has in fact estimated the combined effects of school starting age and age (at the test) " (p. 3).

Yet the debate revolving around school entry age is not just a governmental debate about an institutional rule. In many countries, parents calculate exactly when they will first enroll their children in school—a practice called "red-shirting". Deming and Dynarski (2008) define "red-shirting" as deliberately delaying entrance into academic instruction as a result of a parent's or teacher's decision. Supporters of red-shirting argue this "gift of time" allows children to be more mature and thus benefit more from their academic instruction. In the U.S., the share of six-year old children enrolled in first grade dropped from 96% in 1968 to 84% in 2005. Deming and Dynarski (2008) estimated that two-thirds of this decline was due to redshirting. Compounding this problem is the fact that some parents also seek to accelerate their children, enrolling children that are younger than the legal, minimum entry age.

This chapter examines the impact of delaying the age of entry into school in the case of México. The analysis avoids some of the problems of the previous literature by considering the impact of a government reform law that changed age eligibility in the country. In June of 2006, Mexican education law (Article 65) was revised to change the date governing first grade eligibility. Before the law, children had to be at least 6 years old by September 1st to enroll in first grade. The reform moved the cut-off date from September 1st to December 31st thereby allowing younger students (who were five years old in September but six by the end of December) to enroll in first grade and lowering average entry ages. Because the younger students entered first grade as a result of an exogenous policy change (and not because of the decisions of parents), they are unlikely to differ from the older students except because of the age difference.

Taking opportunity of this natural experiment,, the research in this chapter adopts a a regression discontinuity design to estimate the causal effect of delayed entry into school on student achievement. This quasi-experimental design, which mimics a randomized experiment, allows to estimate the parameters relevant for policy analysis. Section 4.2 summarizes the current literature. Section 4.3 presents a theoretical model where age is incorporated into the Education Production Function (EPF) as an underlying parameter that has an effect on children's cognitive achievement through three different channels, 1) maturation (all dimensions), 2) parental investment (in the form of family inputs) and 3) school inputs. Section 4.4 explains the background and the context delayed school entry in México. Section4.5 describes the research methodology and identification strategy. Finally, Section 4.6 discusses the main results.

4.2 Related Literature

The early studies examining the effect of age delay simply compared student outcomes of students of different ages in a given grade or students of the same age in different grades (see, for example, Stipek and Byler (2001), Stipek (2002) and NICHD and Study (2007)). But due to the practice of redshirting, early school entry may be endogenous and respond to the characteristics of students and parents. More recent studies have sought to deal with these econometric issues by seeking exogenous variations in ages of entry into school, whether as a result of changes in entry age policy within a country, shifts in those policies over time, or through quasi-experimental studies that claim random assignment of students of different ages to a grade cohort. Moreover, these recent studies on the short-term effects of delayed formal education is extensive but inconclusive. Black et al. (2008) argue that there are two main conclusions in the literature: 1) in a same grade, children who delayed school entrance by a year tend to perform better on in-school tests, and 2) among children who are the same age, those who entered school earlier (thus have more schooling experience) perform better than those who have less school experience. Furthermore, the empirical studies tend to use only children in the same grade as counterfactuals to estimate the effect of delaying enrollment by a year. Consequently, for the most part, the evidence tends to suggest that older children do better in school. There is evidence in the field of economics supporting that "readiness" itself is an important factor.

One of the first analyses of school start ages using methods that seek to establish causality was conducted by Datar (2006). In this study, the author estimated the effect of entry age and school age within a grade. Datar (2006) uses two sources of identification: variation in birthdays and variation in state kindergarten entrance-age policies. The results show a significant positive effect of delaying school by a year of about 5.8 points (0.8 s.d.) over baseline math scores at kindergarten. The impact of delaying school by a year on test score gains from the baseline to the spring of the 1st grade was 0.5 points (0.08 s.d.). In addition, Datar (2006) compared students at the same age by using test score trajectories (linear projections of the estimates) indicating that younger entrants perform better by 5.8 points on the standardized tests at the age of 6. The author concluded that these results were driven by the extra year of schooling among younger entrants.

Elder and Lubotsky (2009) extended the methodology used by Datar (2006) to pursue a different interpretation of the age effect. The authors used the same sources of variation as the previous Datar analysis (the distribution of birth dates through the calendar year and the differences across states in kindergarten entrance cut-offs) and concluded that upon entering kindergarten, the gap between the oldest and youngest entrants is explained by an entrance-age effect. Prior to the impact of schooling on cognitive achievement, the oldest entrants scored 5.28 points (0.53 s.d.) higher than the youngest entrants. At the end of kindergarten, the effect of entry age was 8.17 points higher than when the children started kindergarten.

Elder and Lubotsky (2009) finds that the impact of delayed school entry varies by socioeconomic status. In general, the results show that entrance-age effects rise with socioeconomic quartiles. Within the richest quartile, the difference on performance (youngest versus oldest) is higher (23.66 points) than the differences within the poorest quartile (10.65 points). The effect of entry age among the poorest decreased after the end of kindergarten; only a small effect lasted until 5th grade (4.92 points). Nevertheless, the differences over time remained high within the richest quartile. The authors also mention that the age entry cut-offs and birthdays affected the absolute and the relative ages in school. In addition, the variation across states in entry cut-off dates allows variation of relative ages since states with earlier cut-offs, such as September, have an older cohort than those states with later entrance cut-offs, say in December. The effect on average age in school is standardized so as to estimate how the relative age of a child influences student achievement, expressed as $\mathbf{EA_{is}} - \overline{\mathbf{EA}}_{\mathbf{s},-\mathbf{i}}$. The results show that relative age is not a significant factor at the baseline (Fall 1998), but that later the effect of average age is positive and significant, declining after the child enters 1st grade. These results show that relative age may influence learning and other non-academic skills.

Elder and Lubotsky (2009) concludes that "the ratio of the benefit of a year spent out of school to the within school year increases in average test scores is 0.28 (8.17/29) for reading scores and 0.43 (9.98/23) for math test scores" (p. 752). However, the authors emphasize that the systematic increase of school entry ages results in an increase on test scores at the beginning of school life but decreases later, parental investments in pre-schooling are crucial for how the older students do after they enter kindergarten, and the differences in achievement are more prevalent among rich people. All of these issues make the authors emphasize that parents' and teachers' decisions are biased by initial differences in skills unrelated to children's natural abilities.

Most of the recent empirical evidence related to the effects of entry age has been gathered in developed countries such as the United States, including Moussa (2012), who uses data for New York City, Cascio (2008) who uses experimental data from project STAR, Dobkin and Ferreira (2010), using data for Texas and California, and Bedard and Dhuey (2006), who use OECD data, among others.

One of the exceptions is the research by Shapiro on Chile. McEwan and Shapiro (2008) are the only researchers to present evidence on the short-term effects of delayed school entrance on cognitive achievement in a developing country using credible exogenous variation. That is, their study investigated the causal effect of delayed school enrollment on student outcomes in Chile. The authors concluded that 1) Older students are less likely to be retained in the 1st grade by 2%, 2) older students increase test scores by 0.3 to 0.4 s.d. in 4th grade, and 3) older students demonstrate similar effects in the 8th grade.

The basic framework of this research is an education production function whereby dates of birth are treated as exogenous variation and a regression discontinuity is used to estimate causal effects. Moreover, the identification strategy compares outcomes of students who were born in different age cohorts around the cut-offs. In conclusion, McEwan and Shapiro (2008) argue that "the general equilibrium effects of such a policy depend on (uncertain) casual pathways. First, if age-at-test effects dominate, then such a policy would increase early grade test scores without increasing learning, simply because students would be older when tested. The policy could even widen inequality if advantaged students experience greater test score gains while out of school (Stipek, 2002; Elder and Lubotsky, 2009). Second, if relative-age effects dominate, then moving cut-off dates earlier would merely redistribute achievement among students without increasing mean test scores. Third, if absolute-age effects dominate, then raising mean enrollment age would increase mean test scores by improving students' readiness for school" (p. 270).

A more complete analysis of the effects of age on cognitive achievement was conducted by Cahan and Cohen (1989). The study analyzed all the 4th, 5th, and 6th graders attending Jerusalem's Hebrew Language (state-run elementary schools) in 1987. As part of their empirical procedure, Cahan and Cohen (1989) designed IQ tests to be comparable across grade, and test scores were standardized using the standard deviation of the 4th grade. First, the authors point out that the relevant counterfactual of the age effect is a comparison between an age effect and a schooling effect. That is, Cahan and Cohen (1989) realize the tradeoff between delaying school entrance by one year and benefitting from one more year of school. These authors use a regression discontinuity design to explore the age and school effects on cognitive achievement. This quasi-experimental design exploits the exogenous variation in enrollment age at a school as it relates to entry-age laws. This identification strategy assumes the allocation of children to birth dates is random and admission to school is based solely on chronological age. The authors applied the same twelve tests to three different cohorts of students in grades 4 to 6 at the end of the school year and separated age and schooling effects attributed to within-grade and between-grade mean scores differences. Cahan and Cohen (1989) argue that the net effect of age and schooling on intelligence is a comparison between chronological age and schooling effects. The authors define age effects as the difference in mean test scores between individuals chronologically in the same grade and schooling effects as the difference in mean test scores between individuals differing by one year of schooling yet born around the same entry-school date. Cahan and Cohen (1989) finds the coefficients of both age and grade for each of the twelve regressions examined are significant. Of the six verbal tests, the coefficients of age vary from 0.05 and 0.19 s.d. while the coefficients of schooling vary from 0.23 to 0.50 s.d.

4.3 Simple Theoretical model

This section focuses on how to specify and estimate an educational production function (EPF) that examines the effect of age on cognitive achievement in a way which recognizes child development as a cumulative process—a process which itself depends on variety of environmental factors and inherited endowments. The section presents the rationale underlying the age effect on learning and extends the structural theoretical model of cognitive achievement developed by Todd and Wolpin (2003). The model analyzes the factors and processes behind the entry-age effect, time in school, and school inputs on cognitive development. This model suggests that age has an effect on children's cognitive achievement through three different channels, 1) maturation (all dimensions), 2) parental investment (in the form of family inputs) and 3) school inputs. Finally, in addition to this model, there is one major theoretical consideration related to explaining the age-effect on cognitive achievement. This theoretical discussion emphasizes that age can be partitioned into two periods (before and after entry to school) where responses from parents, in the form of resources and other influences, as well as responses from schools are different between these periods.

Age at Entry and the Educational Production Function

Todd and Wolpin (2003) consider an educational production function (EPF) to analyze the relationship among learning, family, and school inputs when children attend school. In this model, cognition is a cumulative process, which starts before children enter school, and is a function of family inputs ($\mathbf{F_{0,i}}$) and innate ability at that point ($\mu_\mathbf{i}$). According to this model, changes in school inputs have a total effect which can be divided into direct and indirect effects through changes in the levels of other inputs (for more details see Todd and Wolpin (2003); p. F8). For example, an increase in one hour of math class per day changes cognitive achievement through 1) the direct effect of one more hour of math, and 2) the indirect effect on achievement of changes in family inputs linked to that child **i** receiving one more hour of math instruction per day (e.g., parental supervision of the child's math homework, more math materials at home, etc.). In this model, cognitive achievement is a function of current and past school and family inputs combined with the child's mental abilities ($\mu_\mathbf{i}$ determined at conception). Moreover, parental and school inputs are a function of the decision rules followed by parents and schools.

More formally, Todd and Wolpin (2003) assume that student achievement, as measured by test scores, is a measure of the cumulative process of knowledge acquisition of the child during time in school **i** residing in household **j** at age **a**. In addition to family (F) and school-related (S) inputs, children's cognitive achievement is assumed to depend on a general reasoning ability, μ_i, which is partly determined by biologically-inherited traits. As Wang and Aamodt (2010) argue that " Individual people's performance on any cognitive test is moderately predictive of their performance on any other cognitive test. These broad correlations between different cognitive skills reflect the existence of a general reasoning ability ” (p.191).

The specification of the educational production function (EPF) generally uses test scores as dependent variables and adds a measurement error ($\varepsilon_{\mathbf{ija}}$) (for more details see Todd and Wolpin (2003); p.F15). The EPF is therefore given by:

$$\mathbf{T_{i,j,a}} = \mathbf{T_a}(\mathbf{F_{ij}}(\mathbf{a}), \mathbf{S_{ij}}(\mathbf{a}), \mu_{\mathbf{i0}}, \varepsilon_{\mathbf{ija}}) \tag{4.1}$$

$\mathbf{F_{ij}}(\mathbf{a})$ is a vector of parental inputs (current and past) at age $\mathbf{a}$ and $\mathbf{S_{ij}}(\mathbf{a})$ is a vector of school inputs (current and past) at age $\mathbf{a}$. Equation 4.1 incorporates chronological age in an EPF as a scale for both biological and psycho-educational developments which impact family and school inputs. Todd and Wolpin (2003) argue that “ The $\mathbf{a}$ subscript on $\mathbf{T_a}(\cdot)$ allows the impact of inputs and of the genetic endowment to depend on the age of the child” (p. F16). This model provides a framework to understand the role age plays in the child’s cognition.

The Age Effect. Under this model, chronological age has a non-negative relationship with cognitive achievement, $\frac{\delta \mathbf{T_{ija}}}{\delta \mathbf{Age}} > \mathbf{0}$. Three different channels by which age has an impact on test scores can be analyzed. That is, the total effect of age on cognitive achievement is the sum of a direct-age effect plus an indirect family-age effect and the schooling-age effect. Without loss of generality, the total effect of age on cognitive achievement is expressed as:

$$\frac{\mathbf{dT_{ija}}}{\mathbf{dAge}} = \frac{\delta \mathbf{T_a}(\cdot)}{\delta \mathbf{Age}} + \frac{\delta \mathbf{T_a}(\cdot)}{\delta \mathbf{F_{ij}}} \frac{\delta \mathbf{F_{ij}}}{\delta \mathbf{Age}} + \frac{\delta \mathbf{T_a}(\cdot)}{\delta \mathbf{S_{ij}}} \frac{\delta \mathbf{S_{ij}}}{\delta \mathbf{Age}} \tag{4.2}$$

The first component of the total effect is the direct effect of age holding constant other factors; that is, the effects of biological maturity on test scores. This effect can be visualized as a shift of the production function (T), over time, holding all inputs constant. The second component is the return to school inputs on achievement due to a child entering one year older. Parental inputs are provided since the moment of birth, whereas school inputs are a function on the time in school and age in the education production function (Todd and Wolpin, 2003).

Decomposing the Age Effect in two periods. While this model may provide a solid background for the analysis of cognitive achievement in general, it does not distinguish between what the effect of age on cognition is before and after the child enters school, a crucial issue to separate in an analysis of changes in school entry age. An extension of this approach follows Black et al. (2008) which state that the age at which a student takes a test can be divided into the school starting age and the subsequent years of schooling.

$$\mathbf{Age} = \mathbf{SchoolTime}(\mathbf{SA}) + \mathbf{EntryAge}(\mathbf{EA}) \tag{4.3}$$

If the model assumes that age can be partitioned into these two periods (before and after entry to school), an EPF including these periods is obtained by incorporating the conceptual distinction in equation 4.3 into equation 4.2 in the following way:

$$\mathbf{T_{i,j,EA,SA}} = \mathbf{T_{EA,SA}}(\mathbf{F_{ij}}(\mathbf{EA}), \mathbf{S_{ij}}(\mathbf{EA}), \mathbf{F_{ij}}(\mathbf{SA}), \mathbf{S_{ij}}(\mathbf{SA}), \mu_{\mathbf{i0}}, \varepsilon_{\mathbf{ija}}) \tag{4.4}$$

$\mathbf{F_{ij}}(\mathbf{EA})$ is a vector of parental inputs starting at the moment of birth up until the age that a child starts school, $\mathbf{EA}$, and $\mathbf{S_{ij}}(\mathbf{EA})$ is a vector of school inputs at the entry age $\mathbf{EA}$ (which is zero before the start of school).On the other hand, $\mathbf{F_{ij}}(\mathbf{SA})$ is a vector of parental inputs supplied after the child enters school $\mathbf{SA}$, which start at entry age and ends at the time the child takes the achievement test which is the outcome of the production function being examined, and $\mathbf{S_{ij}}(\mathbf{SA})$ is a vector of school inputs supplied after the child enters school, up to the age at which the child takes the achievement test $(\mathbf{SA})$. The decomposition into two periods allow learning to be analyzed at two different stages of development: 1) learning with family inputs only, which happens before entry to school occurs, and 2) learning in a school environment.

Using this theoretical framework, the total effect of age on cognitive achievement is modeled as:

$$\mathbf{\frac{dT_{ija}}{dAge} = \frac{\delta T_{ija}}{\delta EA} + \frac{\delta T_{EA}(\cdot)}{\delta F_{ij}}\frac{\delta F_{ij}}{\delta EA} + \frac{\delta T_{SA}(\cdot)}{\delta SA} + \frac{\delta T_{SA}(\cdot)}{\delta F_{ij}}\frac{\delta F_{ij}}{\delta S_{ij}}\frac{\delta S_{ij}}{\delta SA} + \frac{\delta T_{SA}(\cdot)}{\delta S_{ij}}\frac{\delta S_{ij}}{\delta SA}} \tag{4.5}$$

Where $\frac{\delta \mathbf{T_{EA}}(\cdot)}{\delta S_{ij}}\frac{\delta S_{ij}}{\delta EA} = 0$

The total effect of age is divided into an entry-age effect and an age-school effect. From a theoretical perspective, the first two components of the equation are 1) the impact of being older at entry age on student achievement by being more cognitively mature (which symbolically is represented by how an increase in entry age, EA, shifts the production function T, and 2) the effect of entry-age on family inputs since, by entering school a year older the child will have an extra year of parental inputs. The rest of the equation is the school-age effect which is divided into 1) the age-at-test effect, which measures the impact on student achievement of the maturity gained by a child by being in school for a longer period of time, 2) the age-school inputs effect and 3) the family-school age input effect. Entering a year older may change the decision rule relative to family inputs and school inputs, thus affecting these components of the EPF. For example, parents may allocate fewer inputs during the first years of education due to the extra cost of having had the child out of the school, or teachers may adjust the curriculum during the year due to the child's performance.

This decomposition defines the total effects of age as the effect of age at the moment of starting school (entry-age effect) and the effect of age during school. The entry age effect allows heterogeneity among test scores before the first day of school. The channels through which this effect works are the biological maturation of the child and the resources during an extra year out of the school. For example, children face a decision to enter school when they are eligible albeit less mature and with fewer parental inputs, or a year later with a higher level of maturity plus an extra year of family inputs. The school-age effect is the effect on mental capacity at the moment of the test plus the effect of parental and school resources on test scores as a response to the delayed enrollment.

To sum up, this theoretical model emphasizes four different channels though which delaying a year of schooling affects the cognitive achievement of children using an EPF: 1) parental investments prior to formal education in the form of prior skills, 2) adjusted family inputs during school time, 3) adjusted school inputs during school time, and 4) direct entry-age and age-at-test effects (age maturation effects).

4.4 Background and the context delayed school entry in México

4.4.1 Data and Sample

The analysis in this dissertation uses two main sources of data: the National Evaluation of Academic Achievement in School Centers (ENLACE) and the administrative School Census data (SCD- 911). These sources of data are produced by the Ministry of Education (ME). México's school census and ENLACE tests have far richer information from assessment information for school, students, and principals.

The National Evaluation of Academic Achievement in School Centers (ENLACE). Since the school year 2005-2006, the Ministry of Education has administered the National Evaluation of Academic Achievement in School Centers (ENLACE) nationwide. ENLACE is now administered annually in April to early June and parents, teachers, principals and other stakeholders know when the exam will be applied (through a document distributed before the start of the school year). This test instrument is objective, standardized and comparable over time, although, it is not comparable across grades (ENLACE technical document, 2010). The ENLACE assessments are in math, Spanish and another subject that varies from year to year (rotative subject), as well as birthdate information. ENLACE is still not administered in two Mexican states due to teacher strikes and the CNTE teachers union. Removing these two states from consideration, ENLACE attains very good coverage. Table 4.1 depicts the population covered by the exam (which excludes Oaxaca and Michoacán from the total number of enrolled students by grade).

There are four types of schools from grades 1 to 6 in México: 1) compensatory schools, 2) indigenous schools, 3) public-general schools and 4) private schools (see Annex Table 4.17 for more details). Compensatory schools are those with a multigrade curriculum and enroll very isolated populations. These schools can decide not to administer ENLACE, resulting in a lack of data for them.

Table 4.1: ENLACE net coverage without Oaxaca and Michoacán

	Third	Fourth	Fifth	Sixth
2006	0.97	1.00	1.02	1.05
2007	0.89	0.90	0.94	0.94
2008	0.91	0.94	0.95	0.97
2009	0.89	0.90	0.90	0.91
2010	0.93	0.94	0.93	0.96
2011	0.93	0.94	0.95	0.97
2012	0.86	0.88	0.88	0.91

Source: Author's calculations using ENLACE and official numbers from SEP

In the Appendix, Table 4.17 details the number of students evaluated since ENLACE started. The 2012 administration numbered over 13 million students between the 3rd and 9th grades. In fact, ENLACE requires the coordination of over 100,000 people to supervise the nation-wide assessment. There are a number of methods used to diminish the risk of cheating. First, teachers cannot administer the exam to their own class and parents cannot supervise their own children. Also, the SEP's Department of Policy Evaluation (the agency in charge of ENLACE before the reforms of the National Evaluation Institute in 2013) used the K-index and Scrutiny methods to detect cheating or suspicious answer patterns. Each subject is tested individually, and ENLACE scores represent the number of correct answers (weighted by the difficulty of the item) on a scale that ranges from 200 to 800 points, with a standardized mean of 500 and a standard deviation of 100. For comparisons over time, 2006 is used as the base year.

ENLACE was not a high stakes assessment until 2010, but since then it has also been used to calculate incentives and promotions among teachers and principals. Moreover, selected schools taking ENLACE are given questionnaires to complete. The questionnaires gather information on principals, parents and students during the school year.

The School Census data (SCD) -

The School Census Data (SCD) is an annual administrative record prepared by principals at the beginning and end of each school year. This census is validated by each state's information department and by the federal department in charge for integrating all the information. The SCD includes geographic school information (precise location of each school) and school inputs during each school year, from infrastructure to teachers' average education. For purposes of this analysis, the SCD data set includes measures of the school inputs students receive during their education as well as data on the distribution of age in each grade, percent of 1st graders who attend kindergarten, repeaters, etc. These data had fourteen rounds from the school year 1998-1999 to 2011-2012.

Other sources of information -

Data regarding the distribution of birthdates vis-à-vis school cut-off dates are derived from the National Health Information System (SINAIS). This data bank contains all the administrative records of births from 1984 to 2011. In addition, the socioeconomic background of students is identified by using a marginality index constructed by The National Council of Population (CONAPO). The CONAPO marginality index uses a principal components analysis with nine variables to measure levels of domestic assets, education and family income at the level of individual localities. This marginality index is a function of 1) the percent of houses without water, sewage, electricity, non-dirt floors or a refrigerator, 2) the percent of the population without a primary education, and 3) family income.

4.4.2 The Context of a Natural Experiment: the School Entry-Age Law

This subsection describes the context of the School Entry Age reform undertaken in México 2006 as well as those changes in the education system that occurred parallel to the reform, such as the kindergarten reform that took place two years earlier. The school entry-age reform had several implications. First, the reform changed and unified the school-entry age across Mexican states. Before the 2006 reform, half of the Mexican states used September 1 as their cut-off-date; after this centralized reform, all states transitioned to December 31. A second implication was the change of incentives on the parental decision rule. Before the 2006 reform, parents could decide to engage in accelerated school entry as well as "red-shirting". After the reform, red-shirting practice was possible but accelerated school entry disappeared. Finally, the reform had a transition period during class size increased.

In June of 2006, Mexican education law (Article 65) was revised to change the date governing 1st grade eligibility: Children had to be at least 6 years old by September 1 to enroll in 1st grade. This reform moved the cut-off date from September 1 to December 31 thereby allowing younger students to enroll in 1st grade and lowering average entry ages. Before the revised date became law, however, there was notable opposition among teachers, researchers and politicians. After all, September 1 had been the cut-off date without modification for at least 40 years. In an interview with the minister for basic education during the discussion and approval of the reform, Lorenzo Gomez Morin mentioned that the reform was due to parental pressures for children to enter 1st grade at a younger age.

Table 4.2 depicts the school entry legislation before and after the 2006 reform. The minimum age to be eligible to start academic school was 6 years at September first before the 2006 reform; now, eligibility covers those at minimum age of 5.6. The distribution of age has shifted to the left because this law also implies a lower expected maximum age.

Table 4.2: Changes in School Entry Legislation

Level	Cutoff until 2006	Min-Age	Max-Age	Cutoff after 2006	Min-Age	Max-Age
Kindergarten	September first	3	4	December 31th	2.6	3.6
First Grade	September first	6	7	December 31th	5.6	6.6

Source: Diario Oficial de la Federación, Martes 6 de Junio de 2006

Before the 2006 reform, parents and other school actors adjusted their behavior in accordance with cut-off dates—in some sense they "gamed" the system. The reform changed the calculus as the new date dis-incentivized those parents who wanted to accelerate their child's entry to school. The minimum school entry age was reduced by 122 days (4 months), redefining what counts as earlier entry. Moreover, those parents who still engage in redshirting, that is, who delay school entry, will enroll children when they are older but they will still be relatively younger when compared to the children involved in redshirting prior to the 2006 reform. Before the reform, children born before September 1st (say in August and July) would be key targets for parents engaging in redshirting, but after the reform it would be children born in November and December who would be key targets. This would be a younger group. But in addition, it is likely that the reform would make the practice of redshirting more common, at least temporarily: if some parents believe their children are too young to enter the first grade, then making the entry age lower would raise the likelihood that even more parents will believe their children are too young to enter first grade. Of course, as parents adjust to the idea of younger first-grade students, the practice may diminish.

Table 4.3 illustrates school entry decisions before and after the 2006 reform.

Table 4.3: Parental and school actors reaction to cutoffs

	Before the reform	After the reform
Parents	Delayed Accelerated	Delayed
States	Accelerate	Consistent with the law
Public schools	Delayed Accelerate	Consistent with the law
Private	Delayed Accelerated	Delayed

Source: Own elaboration

The available evidence is that the Mexican states not only complied with but enforced this new federal cut-off date. There is no detailed information of each student at the exact age they entered first grade. But in third grade students take the ENLACE test, which records their age. Students with an age younger than the appropriate age to be in third grade are classified as early age students. Those students who are age-eligible to attend this grade are named appropriate age students. Finally, those students who are older than the eligible age for third grade are defined as late age students.

Table 4.4 shows the percentage of these three student groups. Because the reforms were implemented in 2006, the law initially applied to that cohort of children who were (i) born between September 2, 1999 and December 31, 2000 and then (ii) entered 1st grade in school year 2006-2007 and then (iii) sat for the ENLACE test in 2009 in the 3rd grade. Earlier cohorts (born in 1997, 1998 and the first two-thirds 1999 generation) were not affected by this reform. Early age students for the school years before the reform (in this case, they took the ENLACE test before 2009) were around 11-12% of the third grade class. Those who delayed enrollment were about 13% of the third grade class (which also included those who repeated 1st or 2nd grade). Technically, Mexican law prohibits children from failing or repeating the first three grades, but repetition and temporary dropouts do happen—at a rate less than 2%.

It can be concluded from this analysis that the law allowed younger students to be enrolled and it ended the practice of school acceleration. On the other hand, it could be implied from the data that the practice of redshirting did not end, and so there remained a substantial proportion of students who were older than the appropriate age after the reforms. In fact the proportion of older students rose temporarily but then declined, which may be a result of parents adjusting their perception of the age at which students should enter the first grade (which motivates redshirting) after the reform. It should also be emphasized that school delay has a variety of reasons. An analysis of the ENLACE data shows that the over-age population –children who entered the first grade at age 7—have on average lower family income, have less kindergarten experience, more siblings, and less educated parents when compared with those who enrolled at age six.

Table 4.4: Classification of entrants over time

	Early	Appropiate	Late
2006	0.11	0.79	0.09
2007	0.12	0.74	0.13
2008	0.11	0.75	0.14
2009	0.00	0.87	0.13
2010	0.00	0.70	0.30
2011	0.00	0.76	0.24
2012	0.00	0.82	0.17
2013	0.00	0.86	0.14

Source: Author's calculations using ENLACE (2006-212)

The reform had some short-term effects on the school system itself. There was a direct impact on class size during the first years of the implementation. The first grade entry age modification allowed more children to enter to first grade for the first time during 2006-2007: those children born from September 1999 to the end of December 1999 were now eligible to enter first grade, and this implied a larger class size during the 2006-2007 school year. But in addition to the entry age reform, state education authorities and schools were forced by federal authorities to enforce an obligatory 3rd grade of preschool reform in 2002, which meant that there would be a greater number of children enrolled in primary school beginning in the school year 2006-2007, three school years after this reform was approved. This also bumped upwards the enrollment rates in first grade, as seen in Figure 4.1.

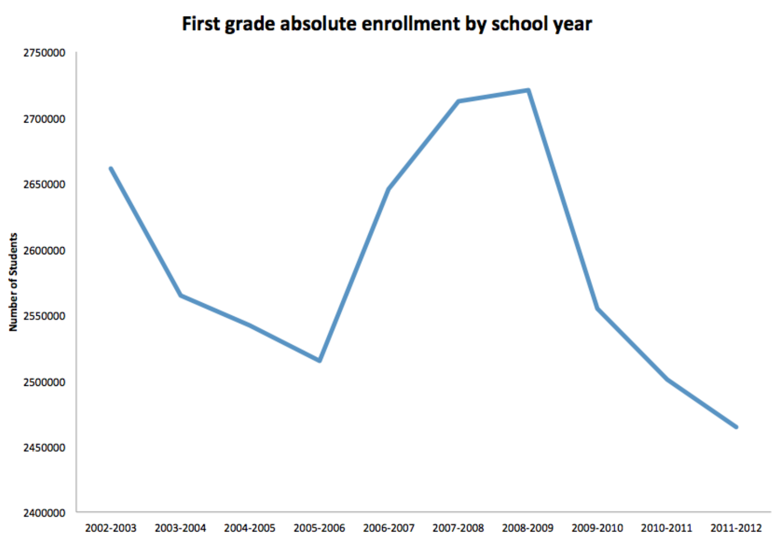

Figure 4.1: First Grade Absolute Enrollment by school year.Source:Author's calculation using SEP data

This figure also shows the overall declining enrollment trend in first grade. According to the SINAIS information, since at least 1997, the Mexican birth rate has declined: in 1997, 2,285,050 Mexicans were born while in 2004 only 2,034,460 were born. This has led to a reduction in enrollment, An appendix shows enrollment rates during this time period. Note finally that state education authorities, parents, teachers and children all adjusted to the 2006 reform over a period of years. The effects could not been expected to be restricted just to the year of the reform itself.

Table 4.5 indicates that delayed enrollment is a common practice at all levels of marginality. However, this practice is more prominent with high and very high marginality. There is no evidence that

Table 4.5: Marginality and Late age students in third grade

	Very Low	Low	Medium	High	Very High
2006	0.07	0.08	0.11	0.14	0.20
2007	0.11	0.11	0.15	0.18	0.20
2008	0.11	0.11	0.16	0.19	0.23
2009	0.10	0.11	0.15	0.18	0.22
2010	0.30	0.26	0.33	0.33	0.35
2011	0.23	0.20	0.26	0.28	0.32
2012	0.16	0.15	0.19	0.22	0.26
2013	0.12	0.12	0.15	0.18	0.23

Source: Author's calculations using ENLACE

there are gender differences in school delay. Gender discrepancies appear only with low marginality schools (that is well-off localities) where the percentage of male late-age students attending 3rd grade is 4% greater than female late-age entry. There are substantial differences, however, among different types of school. For instance, community and indigenous schools have a greater percentage of students enrolling at late entry. [1]

Figure 4.2 delineates a timeline of enrollment before and after the school entry-age reform of 2006. In order to enter 1st grade, parents must enroll their children during a national week of registration every February (though there are exceptions due to migration or special cases which permit registration just before the start of the school year). But because of the 2006 reform, the 2005-2006 cohort only included those born between September 1, 1998 and September 2, 1999 while the 2006-2007 cohort included a greater number of students. As Figure 4.2 illustrates, the 2006-2007 schools comprised students born between September 1, 1999 and January 1, 2001—a longer period of time. By contrast, the 2007-2008 cohort was composed only by those born in 2001.

[1] As the marginality index measures poverty in smaller geographical units rather than in households, it is only possible to investigate the relationship between mean poverty scores and the marginality index at state level. The value of 0.90 obtained for the correlation coefficient reveals that mean poverty score is highly correlated with the marginality index. As expected, the main reason is that the two indices include common indicators of deprivation.

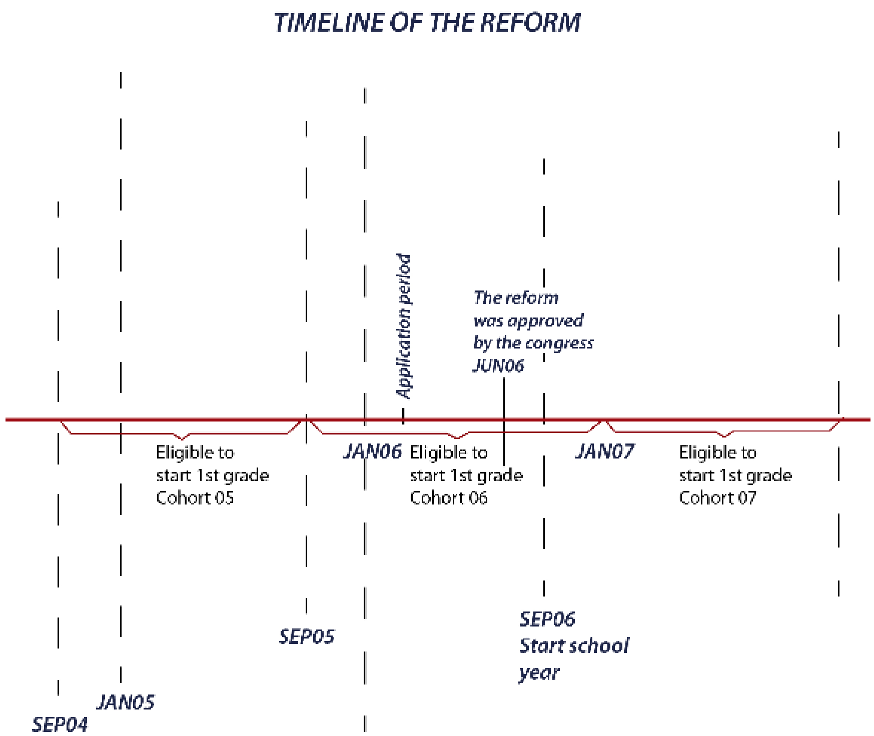

Figure 4.2: Timeline of the School Entry Age Reform. Source:Own elaboration

It is important also to recognize that, prior to the 2006 law, each state observed its own age cut-off date. Table 4.6 depicts the variability of these school entry cut-off dates across states and time. In 2007, nine states had already implemented a December 31 minimum school-entry age cut-off (resulting in greater uniformity among different cohorts). Finally, by 2012, all states conformed to the same nationally mandated cut-off date. Figures 4.14 and 4.15 in the annex illustrate this point.

Table 4.6: State variation in school entry cutoff

	2007	2008	2009	2010	2011	2012	2013
1-Jan	9	7	7	17	28	32	32
1-Sep	14	16	17	10	2	0	0
1-Oct	6	6	4	3	1	0	0
1-Nov	3	3	4	1	0	0	0
Total	32	32	32	31	31	32	32

Source: Author's calculations using ENLACE (2006-213)

4.4.3 Variation in the number of instructional days

According to Article 12 part 2, the federal education ministry mandates a 200-day school year, establishes the national school calendar (detailing exactly when in late August classes start, when in early July classes end, school breaks, long vacations and when registration week and evaluation week occur) and publishes this calendar in its federal newspaper. (Article 51 permits individual states to adjust these dates to suit local contexts and publish locally specific dates in their state newspaper.) Table 4.7 depicts these dates between school years 2005-2006 and 2012-2013 [2].

At the end of each school year, all students in grades 3 to 9 sit for the ENLACE exam. The column entitled 1st-ENLACE specifies the number of days since each generation started first grade until the day of the ENLACE exam in third grade. By the time of their ENLACE exam, the 1998-1999 cohort averaged fewer school days (only 966) compared to other cohorts. Using this cohort as a basis, an "extras days" variable was defined as the number of school days greater than the 1998-1999 cohort.

Agüero and Beleche (2013) analyze ENLACE data over the first three years of its application using instructional days as a source of exogenous variation. These authors estimated the effects of school year length on student performance, and found that average ENLACE test scores increased 0.04 to 0.07 s.d. per extra 10 days of instruction. In that study, extra days of classes are defined as those extra days during a specific school year. The authors claim that their results are controlled for time trends and school time-invariant unobserved characteristics. However, two potential endogenous sources of variation may limit their empirical strategy: (1) variation in state school entry cut-off dates, which generates differences in the average age of students in any grade across states, a matter ignored in their paper, and (2) compulsory preschool for those cohorts entering 1st grade

[2] In February of 2014, SEP and INEE agreed to cancel ENLACE in the school year 2014 but they claimed that ENLACE will be updated and applied in 2015

after the 2005-2006 school year, a reform that was noted earlier and which implies that the cohort with the fewest days of instruction (1998-1999) had more students with third grade of kindergarten since this generation was the first one to be under compulsory pre-school education.

Table 4.7: Eligible generation, school days and ENLACE test

Generation	1st grade	3rd grade	Start 3rd	End 3rd	1st-ENLACE	ENLACE	Extras
Sep1996-Sep1997	8/18/03	2005-2006	8/22/05	7/6/06	1024	6/7/06	58
Sep1997-Sep1998	8/18/04	2006-2007	8/21/06	7/6/07	980	4/25/07	14
Sep1998-Sep1999	8/22/05	2007-2008	8/20/07	7/4/08	966	4/14/08	0
Sep1999-Dec2000	8/21/06	2008-2009	8/18/08	7/3/09	978	4/25/09	12
Jan2001-Dec2001	8/20/07	2009-2010	8/24/09	7/9/10	975	4/21/10	9
Jan2002-Dec2002	8/18/08	2010-2011	8/23/10	7/8/11	1010	5/25/11	44
Jan2003-Dec2003	8/24/09	2011-2012	8/22/11	7/6/12	1018	6/7/12	52
Jan2004-Dec2004	8/23/10	2012-2013	8/20/12	7/5/13	1017	6/5/13	51

Source: Own elaboration using the official school calendar by SEP

Agüero and Beleche (2013) cite two states that (with permission of the federal authorities) did not follow the official school calendar: Aguascalientes and Sinaloa. Aguascalientes changed the days of the evaluation week due to a local festival (celebrated since 1828), and in school years 2008-2009 and 2009-2010, Aguascalientes administered ENLACE in a different week (May 20 in 2008-2009 and May 6 in in 2009-2010). In school years 2005-2006, 2006-2007 and 2007-2008, Sinaloa started classes one week later (due to high temperatures in late August). At the national level, ENLACE 2009 (for school year 2008-2009) was planned for the last week of April but canceled due to an outbreak of the H1N1 influenza virus. In response, the Ministry of Education rescheduled ENLACE in three phases: (1) May 12 to May 14 in Baja California, Baja California Sur, Coahuila and Veracruz, (2) May 15 to May 18t in Zacatecas, Jalisco, Hidalgo and Chiapas, and (3) May 18 to May 22 in the rest of the country.

4.4.4 Data for the analysis

The Ministry of Education identifies all Mexican schools by assigning each a unique number. In addition, each student is assigned a number. These numbers are used when aggregating and comparing data sets.

The data set utilized in this dissertation includes math and Spanish test scores for third grade students in the school years 2005-2006 through 2012-2013, by year of birth. The empirical methodology analyzes cohorts defined by students' year of birth, including cohorts entering first grade before and after the school entry reform law was implemented. More specifically, the data includes students for the school years starting in 2005 to 2012, which comprises eight student cohorts born between 1997 and 2004. Unfortunately, the ENLACE data during this period are partially incomplete. Exact dates of birth (month/day/year) are known for only 65% (120,0846 students) of the 2006-2007 enrollees. (By comparison, a minimum of 97% of birth dates are known for the other years.)

There are no data available specifying the exact entry age of 1st graders. However, their ages can be estimated from information provided when they took the ENLACE test in third grade. Table 4.8 depicts ENLACE rounds for 3rd graders by their birth cohort. The enrollment rate per cohort before the age-entry reform of 2006 can be divided in two, those who were born between January 1 and September 1 and those who were born between September 2 and December 31. For example, about 56% of the 1997 birth cohort, those who were born between January 1 and September 1, attended third grade in the school year 2005-2006 while the rest of this cohort attended third grade after. The situation changed after the 2006 reform: the 2001 birth cohort attended at a rate of 76%, while the rest of the cohort attended 3rd grade over the age eligible to them. After that, subsequent cohorts have increased their enrollment in the year they became eligible to attend school with the 2002 cohort attending the 2011-2012 school year at a rate of 85%.

Table 4.8: Third grade attendance by year of birth

School year	1997	1998	1999	2000	2001	2002	2003	2004
2005-2006	0.56	0.0013	0	0	0	0	0	0
2006-2007	0.36	0.66	0.0017	0	0	0	0	0
2007-2008	0.06	0.28	0.66	0.0008	0	0	0	0
2008-2009	0.02	0.04	0.28	0.69	0.0007	0	0	0
2009-2010	0.01	0.01	0.04	0.26	0.76	0.0007	0	0
2010-2011	0.001	0.003	0.01	0.04	0.21	0.85	0.0007	0
2011-2012	0	0.001	0.002	0.01	0.03	0.13	0.89	0.0007
2012-2013	0	0	0.0002	0.002	0.01	0.02	0.11	1.00
Total	1458501	1946236	1981753	2053835	2018067	1992465	1799251	1628048

Source: Author's calculations using ENLACE (2006-213)

ENLACE cannot claim to achieve complete coverage of the Mexican education system. Most of the missing data are clustered in isolated schools, new schools, or states which do not comply with the evaluation system. Table 4.18 in the Appendix illustrates this latter point: the participation of Oaxaca and Michoacán in ENLACE is so low that their numbers lose statistical validity. For these reason, these two states were removed from the data analysis. Similarly, the more isolated multigrade schools are not well represented in ENLACE.

Table 4.9 provides a picture of schools' relative socioeconomic status via a marginality index. There is some variation over time but very little Overall, around 46% of the total population lived in a very low marginality locales; 21% were concentrated in localities with low marginality; 11% of the population lived with medium marginality and the rest (22%) lived under conditions of high or very high marginality.

Table 4.9: Marginality Index by year of birth

Marginality	1997	1998	1999	2000	2001	2002	2003	2004	National
Very Low	0.46	0.43	0.42	0.42	0.42	0.42	0.43	0.42	0.46
Low	0.23	0.23	0.23	0.23	0.23	0.23	0.23	0.24	0.21
Regular	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.11
High	0.17	0.19	0.20	0.20	0.20	0.20	0.19	0.19	0.20
Very High	0.03	0.05	0.06	0.06	0.06	0.05	0.05	0.05	0.2

Source: Author's calculations using ENLACE and CONAPO 2010

Table 4.10 provides mean math and Spanish scores by birth cohort. The 1997 birth cohort had the lowest mean score in math and Spanish. (Most of this cohort was in the 3rd grade in school year 2005-2006—the base year of the ENLACE scale). The mean scores in math and Spanish have increased in subsequent years with a 0.88 s.d. increase in math and 0.52 s.d. increase in Spanish between the 1997 and 2004 birth cohorts. Table 4.10 also shows the "extra days" of schooling in each cohort. Recall that the variable "extra days" of schooling is the number of instructional days each cohort had before taking ENLACE.[3] The cohorts with more extra school days were the 2003 and 2004 birth cohorts—with 50 days more school prior to the ENLACE test. Finally, the average years of preschool have increased over these generations due to the reform of kindergarten in 2002.

Table 4.10: Descriptive statistics by year of birth

Year of Birth	1997	1998	1999	2000	2001	2002	2003	2004
Math	507	515	520	529	533	545	572	595
Spanish	507	517	525	537	546	555	556	559
Extra days	38	10	4.38	12.85	17.78	45.16	52	51
Average years K	2.17	2.19	2.28	2.38	2.38	2.40	2.36	2.38

Source: Author's calculations using ENLACE (2006-213)

The data use in this analysis permit the internal validity of the results for the Mexican context for the population impacted by identification strategies, and also minimize the selection problems.

4.5 Methodology and Empirical Strategy

4.5.1 The identification strategy: the cutoff approach

The identification strategy used in the current analysis is the "cut-off approach" whereby some children must attend school one whole year later –by accident–than their cohort because of school start age policy (Bedard and Dhuey, 2006; Elder and Lubotsky, 2009; Fredriksson and Öckert,

[3]This number is constructed using the total days of schooling of each student during grades 1, 2 and 3 prior to taking the ENLACE exam, and is compared to other cohorts with fewer or greater extra days of instruction by the time of the ENLACE test: Cohorts with more days of instructions have extras days of schooling.

2005; Datar, 2006; Dickert-Conlin and Elder, 2010; McEwan and Shapiro, 2008; Cahan and Cohen, 1989; Cahan and Davis, 1987; Bjorklund, 2011; Black et al., 2008; Deming and Dynarski, 2008; Barnsley and Thompson, 1988). This identification strategy compares the outcomes of students who were born just before the cut-off to those born just after the cut-off (with the assumption that birth dates near such cut-offs are random). This strategy allows us to observe schooling outcomes and how these outcomes are affected by entry-age cut-off dates.

The cutoff approach in Economics uses as counterfactual individuals in the same grade who differ in age due to the entry law (two different birth cohorts). This cut-off strategy is used in the analysis in this dissertation. Maintaining the grade constant, the strategy compares the older students who delayed enrollment due to the law with the younger students, with a focus on those who were born around the entry-date of formal education. The only difference is one year in age. However, there are two potential groups that comply with this strategy. Table 4.11 illustrates these two groups. Maintaining the same birth cohort and grade constant, the first strategy compares the older students who delayed enrollment due to the law with the younger students from a previous school year. For example, it compares the outcomes in third grade of students who were born in the same cohort but because they were slightly younger or older they ended up entering first grade with one year of difference (which also means they reach third grade in different school years). The second strategy is to also maintain the grade constant, but compare the older students who delayed enrollment due to the law with the younger students in the same school year, with the two groups belonging to two different birth cohorts. For example, one can compare the outcomes of the older, school-delayed students in third grade with those of the younger students in that same grade (who entered on-time) in a given school year.

Table 4.11: Same Grade, counterfactual groups

	Intra-Age	Inter-Age
Oldest	School year $t+1$, Birth Cohort bc	School year t, Birth Cohort $bc+1$
Youngest	School year t, Birth Cohort bc	School year t , Birth Cohort bc

4.5.2 Validity of the Randomness of the Date of Birth

The literature on this topic uses the "cut-off approach" as an exogenous source of variation, and tends to justify its utility by either assuming (or arguing, see below) the randomness of birthdays before and after a cut-off date. But since parents are typically of aware of the entry age law for starting 1st grade, parents may attempt to control the day the child would be born. This may make dates of birth non-random. However, McCrary (2008) argue that this type of manipulation would not necessarily invalidate the identification strategy. After all, some parents tend to want their child to start school as early as possible (even if younger than the other students) while other parents might want their child to be among the older students in the class. The overall result may not bias birth dates in any given direction, whether younger or older

Nevertheless, such non-random manipulation could be at play, and would threaten the validity of the "cut-off approach". In fact, Bound et al. (1995) share evidence of small differences in health across seasons of birth in the United States—health differences between winter- and summer-born children. According to this literature, parents manipulate the timing of a birth (with the aid of medical technology) so as to maximize benefits and minimize costs for their family. Birth timing vis-à-vis school entry cut-off dates is then, at least theoretically, an avenue for parents to maximize benefits and minimize costs for their family Dickert-Conlin and Elder (2010). Upon inspection, however, Dickert-Conlin and Elder (2010) show there is no parental manipulation of birth timing—including those births under obstetric procedures—in the United States during the period 1999-2004. The authors conclude that parental manipulation with an eye toward school cut-off dates is not significant.

In order to identify potential birth timing discontinuities relative to school cut-off dates in México, the density of births from 1998 to 2007 were analyzed. While many factors affect the timing of a planned birth, those parents who aim to have a child start school at a relatively young age will plan for a birth just before the cut-off date and those who want their child to be relatively older will plan for a birth just after the cut-off day. So, if there are disproportionately more births just before or after a cut-off date—a "birth bubble" surrounding a cut-off date—this is evidence that parents are manipulating birth dates. And while a McCrary test may not work if manipulation is not monotonic, parents who the due(birth) date is close to the cutoff and want to delay school will not act in response of cutoff dates; however, parents who the due(birth) date is close to the cutoff who want their child start at eligible age will try to make sure that the birth is before the cut-off (strategy manipulation).

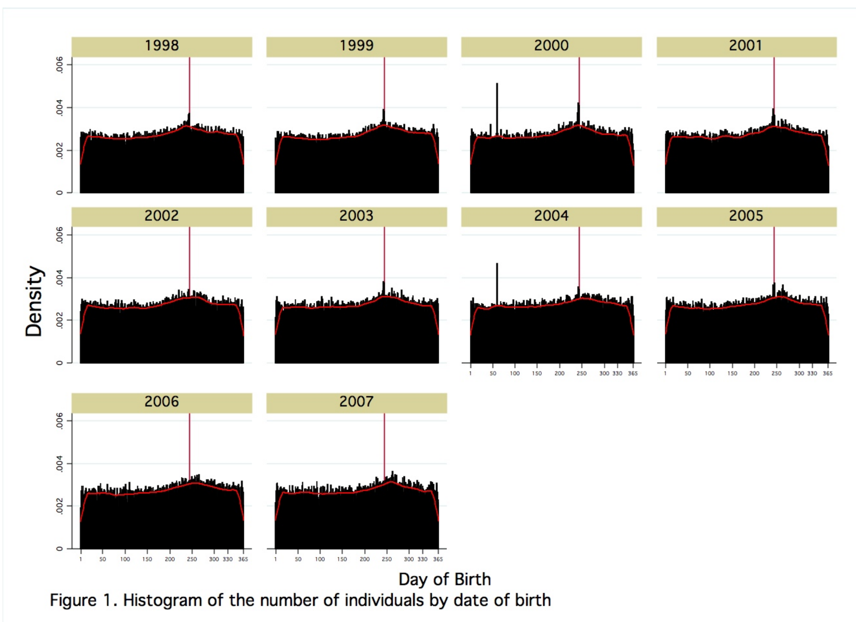

Figure 4.3: Histogram of the number of individuals by date of birth. Source:Author's calculation using SINAIS data

Analyzing Mexican birth certificate records from 1998 to 2008 in México, the continuity of birth density around the cut-off date and the randomness of covariates at the cut-off date were tested. Figure 4.3 presents several histograms of birth dates from 1998 to 2007 and does provide some evidence of a greater density of births on both sides of the cut-off date relative to other calendar dates—with birthdays just prior to the enrollment cut-off often out-numbering birthdays just after the cut-off. All this suggests that parental manipulation of birth timing around cut-off dates is apparently real, and can invalidate assumptions regarding the random distribution of birth dates.

Figure 4.4 highlights the proportion of births for each day in August and September 2007 relative to the annual per day average from 1998 to 2007. Each bar shows the number of births that occurred in one day as a percentage of the average number of births during that year. The vertical line in each graph represents the cut-off day. The births before the cut-off out-number those after the cut-off—further evidence that birth timing manipulation seems to favor pre-cut-off dates rather than post-cut-off dates.

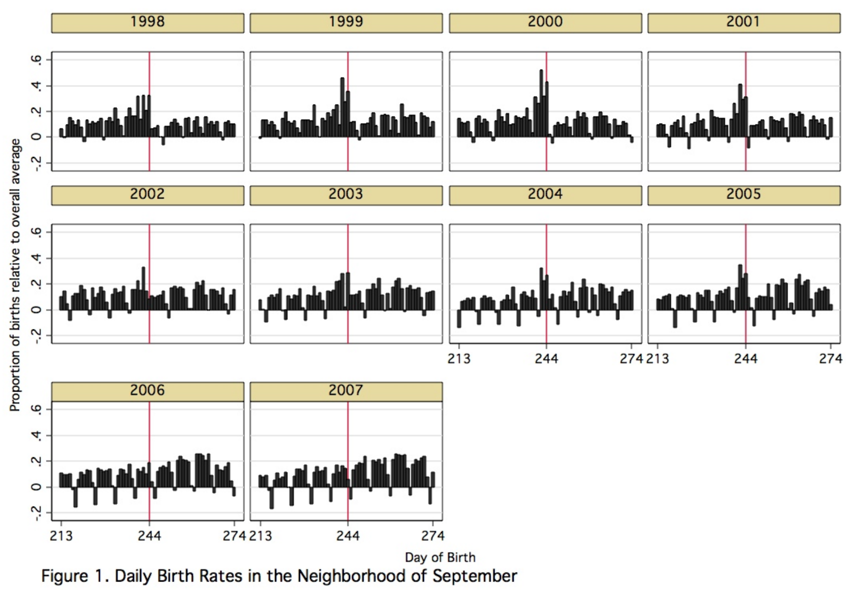

Figure 4.4: Proportion of Births Relative to the year average. Source:Author's calculation using SINAIS data

Closer inspection of the data, however, reveals more subtle patterns. The first three years (1998, 1999 and 2000) indicate a large discontinuity at the school cut-off day of (September 1, the 244th day)—all of which were weekdays (Tuesday, Wednesday, and Friday, respectively). In 2001, the cut-off day fell on a Saturday resulting in 29% more births than on an average day in 2001. Furthermore, in 2002 when September 1 fell on Sunday, the number of births increased only 8% relative to the annual per day average while the days after the cut-off accrued about 10% more births than the average that year. In 2003, a higher discontinuity is found before the cut-off than after the cut-off, and in 2004 and 2005, discontinuities appear again after the cut-off. By 2006 and 2007, discontinuities centered around a September 1 cut-off date are no longer visible; only the cyclical decrease of births on Sundays is apparent.

Figure 4.5 illustrates the average years of schooling of the mother by day of birth.

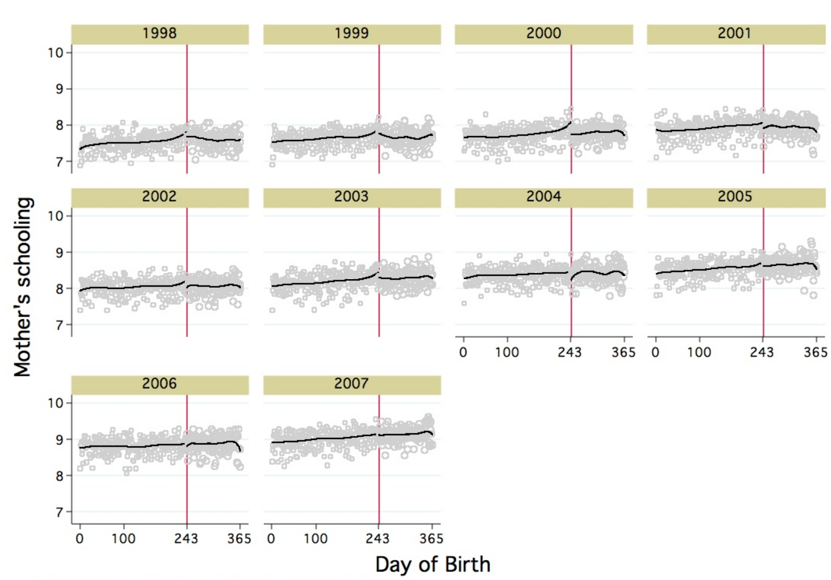

Figure 4.5: Density in Covariate - Mother's schooling. Source:Author's calculation using SINAIS data

These graphs depict inconsistent discontinuities at the September 1 cut-off between 1998 and 2007. The first discontinuity occurs between the last day of August and September 1. This gap varies from about 0.25% more births for the years 1998 to 2001 but decreases after this period. The second discontinuity occurs between the September 1 cut-off and September 2. This gap measures below 0.25% and is not stable over time. For example, the average schooling of mothers bearing children in 1998 was 7.6 years, but mothers who gave birth on Monday, August 31, 1998 had 8.1 years of schooling, and those who had a child on Tuesday, September 1 averaged 7.85 years of education while the average schooling for mothers bearing children on Wednesday, September 2 was 7.65 years—a distribution which peaks before the cut-off date and then consistently drops off. In this way, the data substantiate some sorting around cut-off dates (and by implication, deliberate manipulation of birth timing), but, overall, the data is not strongly consistent and appears to be subject to day-by-day effects. For example, the average schooling in 2003 was 8.2 years, but those mothers who gave birth on Monday, August 31 had 8.2 years of schooling and those who gave birth on Tuesday, September 1 had 8.3 years of education, and mothers who gave birth on Wednesday, September 2 had 8.25 years of schooling—a relatively flat distribution.

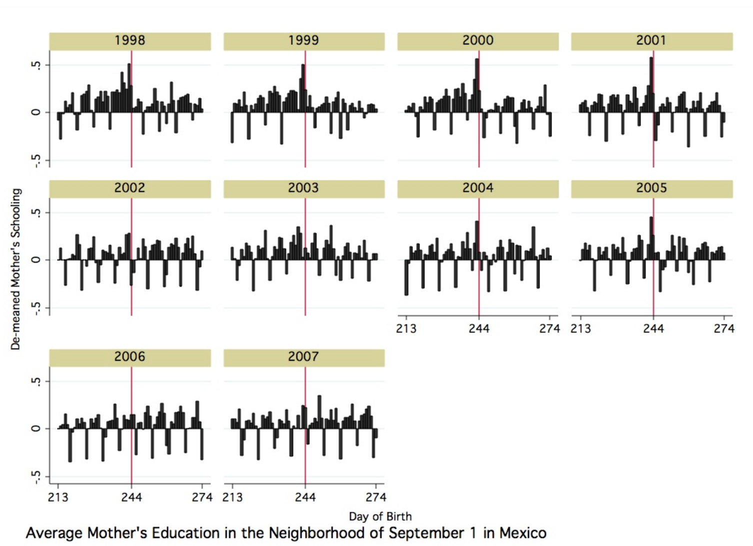

Figure 4.6: Average Mother's Years of Schooling in the Neighborhood of September 1 in México. Source:Author's calculation using SINAIS data

Table 4.12 also shows how the timing of births in México is not random across days—results similar to those reported by Dicker-Colin et al. (2010) in the United States. Dicker-Colin et al. (2010) argue that an even distribution amounts to about 14.3% for each day, yet Sunday births are disproportionately less frequent (and actually becoming less and less frequent during this period). Data relating birth dates to cut-off dates must be interpreted in light of this statistical bias against Sunday birth dates. For example, in 1998, the biggest difference was between Sunday and Monday by 1.83 percent points; in 2007, the biggest gap was between Sunday and Friday by 3.49 percent points. For Sundays, the proportion of births respect with other days of the week was by 1.34 percent points during 1998-2007. The major differences are between Sunday-Monday and Friday-Saturday that suggests that there is a manipulation during these days, but not as much than in these differences in the USA.

Table 4.12: Share of all births by day of week and year, 1998-2007

	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	N
1998	12.92	14.75	14.72	14.51	14.63	14.57	13.91	2,442,276
1999	12.74	14.78	14.68	14.69	14.44	14.93	13.75	2,445,579
2000	12.75	14.66	14.65	14.64	14.55	14.79	13.96	2,509,538
2001	12.37	14.89	14.67	14.7	14.69	14.84	13.83	2,422,265
2002	12.29	14.69	15.01	14.63	14.69	14.97	13.71	2,392,850
2003	12.18	14.85	14.83	14.92	14.53	14.99	13.7	2,323,980
2004	12.04	14.8	14.89	14.77	14.81	15.13	13.57	2,274,897
2005	11.89	14.78	15.02	14.76	14.82	14.98	13.75	2,214,112
2006	11.96	14.63	15.03	14.86	14.84	15.15	13.54	2,134,437
2007	11.66	14.74	14.88	15.02	14.92	15.15	13.63	2,081,248

Source: Author's calculations using SINAIS-SSA data

Overall, the statistical evidence does not support a conclusion of specific parental manipulation of birth timing geared toward cut-off dates. The cut-off strategy is therefore not invalidated. Moreover, on an anecdotal basis, pediatricians in México do not report any systematic manipulation of birth dates near cut-off dates by parents or doctors. As Lee and Lemieux (2009) concludes, "Parents do have some influence regarding when their children are born, but with only imprecise control over the exact date" (p. 347).

4.5.3 Empirical Education Production Function

This section describes the empirical model used to estimate the impact of the 2006 entry-age reform on math achievement. As discussed in the theoretical section, the education production function (EPF) model assumes that age has a direct impact on test scores through a maturity effect, and also an indirect effect on achievement through parental and school inputs (Todd and Wolpin, 2003). The current analysis deploys two different sources of variation to identify the relationship between age and student outcomes in an empirical EPF. First, dates of birth allow comparisons among achievement between those who were born around the minimum-enrollment age. This cut-off strategy allows two treatment groups and one control group. The first pair of treatment-control groups are those who were born around the minimum-enrollment age and attend third grade at the same time but differ in birth cohort. The second pair of treatment-control groups are those who were born around the minimum-enrollment age in the same year and attend third grade at two different points in time. In this second pair, the education production function estimates the impact of the timing of treatment on learning outcomes in the 3rd grade between those who start younger and those who delay enrollment and start older. The analysis allows comparisons of children born in different years but who entered school at the same time as well as students born into the same birth cohort but enrolled in school at different times. The second identification strategy is the school entry reform of 2006 which superimposes a "natural experiment" on the age composition in third grade. Given the new cut-off date, the empirical education production function will benefit from the exogeneity of the age impacts of the reform and provide more reliable estimates on this basis.

Based on these two identification strategies, a regression discontinuity (RD) design is used to estimate the causal effect of age on learning achievement. This quasi-experimental design, which mimics a randomized experiment, allows to estimate the parameters relevant for policy analysis. The RD design estimates the total effect of age on achievement which includes both the direct and indirect effects of the intervention and which is the local average treatment effect on student achievement (Todd and Wolpin, 2003). That is, estimating the age effect includes those factors that changed after the combination of age-eligibility and the decision to enter to first grade. This effect aggregates the impact of factors that are conditional on age, as well as, the effects of age directly. Indeed, Lee and Lemieux (2009) argue that the interpretation of the parameter estimated through regression discontinuity designs with discontinuities in age is a combined effect of all factors that switch on at the threshold.

More specifically, the empirical approach uses a fuzzy regression discontinuity model to estimate the impact of age on math test scores. Even under the September 1st federal cut-off, the entrance age for enrollment was not always followed by parents—or states. Parents in México actually had three options: enroll earlier than permitted, later than necessary or on time. The estimation of an age effect is then potentially distorted due to both underage and overage children. And this distortion is not random: Underage children are typically brighter while overage children typically perform worse (Cahan and Cohen, 1989). In particular, cut-offs create incentives for delays and acceleration of school entry. As a result, Cahan and Cohen (1989) argue that "the relative frequency of grade misplacement is likely to be related to month of birth, being particularly high near the cut-off point. Cook and Campbell (1979) discuss this possibility as a fuzzy cutting point" (p. 1242).

Fuzzy RD design, required by the heterogeneity of parental decisions regarding accelerated age and delayed entry, uses a Two Stage Least Squares (TSLS) estimation strategy, which is the method adopted in this dissertation. TSLS estimates will be used so that the source of identification is the variation in the age-at-test that results solely from differences in birth dates. This TSLS model identifies local average treatment effects (LATE) among children whose actual age is affected by their predicted age.

Another issue to deal with is the fact that some Mexican states were following the 2006 entry law cut-off even before the law was adopted. That is, different states had different cut-offs before the reform. Because of this, the estimation below includes state fixed effects to compare birth cohorts in the same state over time. In this way, the estimates will be weighted estimates of each state's regression discontinuity.

Empirical Model -

Using dates of birth for cohorts from 1998 to 2004, a variable DB is defined as the number of days relative to January 1. For example, for a child born on January 1, 1998, DB is equal to $x = 0$. For an individual born on December 31, 1998, DB is equal to $x + 364$. For an individual born on January 1, 1999, DB is equal to $x + 365$. School entry cut-offs have two direct effects on learning: the composition of each classroom and the heterogeneous responses parents, school actors and students have to educational inputs. Children born around cut-off dates attend school in two “artificial” school cohorts: one composed by the same birth cohort and the other composed of two different cohorts. When the cut-off occurs on December 31, all the students belong to the same birth cohort—and the oldest is 364 days older than the youngest. When a cut-off date occurs somewhere during the calendar year, the comparison between the oldest and youngest is equal to a comparison between those who delayed a year of school and those born at day x. Due to the cut-off date, those who enter school at the minimum entrance age belong to a younger birth cohort x+1.

Four thresholds per birth cohort were defined: September 1, October 1, November 1 and December 1—and one more between birth cohorts, January 1. The total number of dummies $D_j = 1(DB \geq \overline{DB})$ where $\overline{DB_j}$ refers to each specific school entry cut-off. Moreover, any potential bias due to the presence of underage and overage children is identified.

Two Stage Least Squares (TSLS) estimation strategy consists of two stages. That is, the empirical EPF, which incorporates imperfect-compliance, is a system of equations where the first stage is a function of each of the dummies defined by the cut-off dates.

First Stage.

$$\hat{A_{i,bc}} = \beta_0 + D_j\beta' + f(DB_j) + \nu_i \tag{4.6}$$

where $\hat{A}$ is the predicted age at test of a child i of birth cohort bc. D is a dummy that $D_j = 1(DB \geq \overline{DB})$, $f(DB)$ is a piecewise quadratic polynomial.

where $f(B)$ is:

$$f(B) = \sum_{k=1}^{2} \gamma^k DB^k + \sum_{k=1}^{4} \sum_{k=1}^{2} \gamma_j^k D_j(DB - \overline{DB_j})^k \tag{4.7}$$

γ^k=coefficients on polynomial terms

Second Stage.

A second equation is used to estimate the causal effect of a one-year increase in enrollment age on math scores. β_1 is the local weighted average treatment effects (LATE) of students with birth dates near September 1st and who are induced to delay enrollment. It can be interpreted as an "intent-to-treat" effect.

$$T_{i,t,bc} = \beta_0 + \beta_1\hat{A}_i + f(DB_j) + \beta_2 X_{i,t} + \varepsilon_{i,t} \tag{4.8}$$

where $\hat{A}$ is the predicted age at test of child i, D is a dummy that $D_j = 1(DB \geq \overline{DB}$, $f(DB))$ is a piecewise quadratic polynomial, $X_{i,t}$ represents a vector of past and current school characteristics and child characteristics and $T_{i,t}$= Test scores of children i of age t in third grade.

The causal effect of delaying one year of formal schooling on achievement is β_1 which includes the direct and indirect effects of age on the EPF discussed in the theoretical section. The covariates of the analysis include gender, type of school, marginality index, pupil-teacher ratio of the student‘s classroom, and percent of teachers with university or more at the school. Standard Errors are clustered at the school level. The empirical strategy also evaluates the impact the 2006 reform. The first set of specifications is the system of TSLS equations used to estimate the local average treatment effect of age on achievement at each cut-off date across three periods, defined as before the reform (2006-2008), during the reform (2009-2011) and after the reform (2012-2013).

The issue of states adopting different cut-off dates was mentioned earlier and is incorporated into the model with state fixed effects. One of the implications of having states with older school children than others –at least before the 2006 federal reform unified such cut-offs– is that average test scores at the state level may be influenced by those age differences, providing misleading cross-state comparisons. In this regard, it is more appropriate to compare performance within states or between states that have the same cut-off date.

Also, the estimation includes standard errors clustered at the school level. As Alvarez et al. (2007) mention, “It is expected that the scores among students in the same school will be correlated. The reason is that students enrolled in the same school are usually more similar to one another in behavior and characteristics than students enrolled in different schools. In other words, one would expect that student performance for given school factors would increase in order for those school variables to increase or improve, but one might also expect the variation on average school performance to increase as school factors increase or improve” (p. 5). Another issue that the current analysis investigates relates to the exogenous effects of school entry reform on the distribution of ages. That is, the 2006 reform affected the average age of the classroom and it therefore altered the individual students’s relative age in comparison with his or her peers. As Elder and Lubotsky (2009) argues, the delay of school enrollment has an effect on the average age composition of the classroom, and it affects children's peers, a factor that influences student achievement. Econometrically, age peer effects should be included, and the EPF should include the average entry age of the class $\overline{EA}$ to estimate the age peer effect. Equation 4.9 defines the second stage in this case:

$$T_{iyb} = \alpha + \beta_1 A + \beta_2 \bar{A} + f(DB_j) + \beta_2 X_{i,t} + \varepsilon_i \tag{4.9}$$

This is equivalent to the following model, with $\beta_1 = \alpha_1 + \alpha_2$ and $\beta_2 = -\alpha_2$ (For more details see Elder , p. 668)

$$T_{iyb} = \alpha_1 A + \alpha_2 \left(A - \bar{A}\right) + f(DB_j) + \beta_2 X_{i,t} + \varepsilon_i \tag{4.10}$$

4.6 Results

Variation in enrollment age related to changes in age-entry law arises because an exogenous event causes some children to enter school younger than others. The empirical relationship between age-entry laws, the 2006 age reform and 3rd grade ages found in this dissertation suggests that school entry policies had an effect on school outcomes. These are the results.

4.6.1 Graphical Analysis

First Stage

Figure 4.7 depicts the relationship between average age at test and date of birth. The average age at test was calculated taking into account dates of birth and the day the test was taken. The graph shows the expected value of age on a particular day of the year. Reviewing the conditional expectation of age at test, there is a negative relationship between age at test and date of birth for those born between January 1997 and September 1, 1997. For those born after September 1, 1997, there is an increase in age at test until the end of the year. In addition, there are discontinuities in October and November 1997 due to the fact that some states used these months as their cut-off date. A similar pattern is obtained for those born in 1998, 1999 and 2000. The figure also shows that those who were born between 2001 and 2004 had a lower age at test than previous generations. The solid line plots fitted values from the piecewise spline.

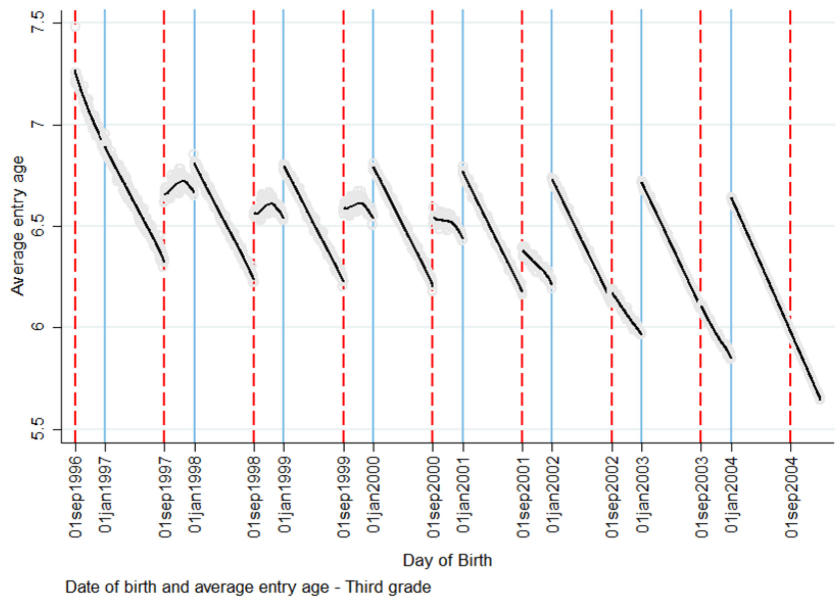

Figure 4.7: Average Entry Age by date of birth. Source:Author's calculation using ENLACE

Second Stage

Figures 4.8 and 4.9 illustrate the reduced-form discontinuity analysis for 3rd grade math and Spanish student achievement, respectively. The math graph shows a negative relationship between math scores and dates of birth before September 1, 1997. Subsequently, there is a substantial nonlinear increase until January 1, 1998. From January 1 and September 1, 1998, the negative linear relationship reappears, and thereafter, the nonlinear relationship between date of birth and math scores resurfaces. After that, the gaps after September 1 decrease. For the birth cohorts who started

1st grade after the reform, there is no discontinuity centered around September 1, and the figure displays a fitted quadratic relationship between math scores and dates of birth after September 1. In fact, the shape of the fitted relationship is very different to the left of September 1 than to the right for each of the cohorts before the 2006 reform. Moreover, after the reform, the relationship between age at test and math achievement is negative across calendar days for each birth cohort. Finally, the discontinuities are centered around January 1.

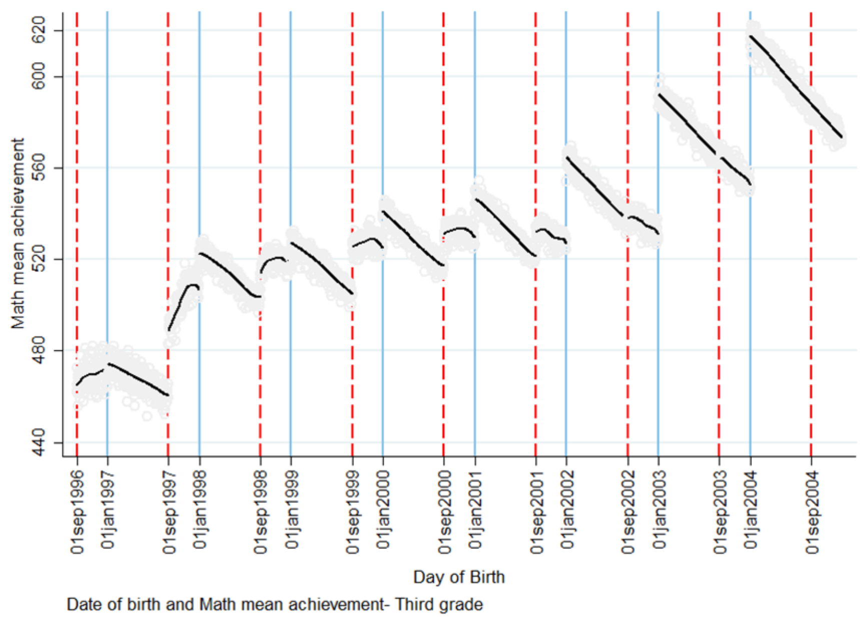

Figure 4.8: Average Math performance by date of birth. Source:Author's calculation using ENLACE

Figure 4.9 illustrates the relationship between Spanish test scores and dates of birth. A pattern similar to the math graph obtains although Spanish did not increase as much as math for the later birth cohorts.

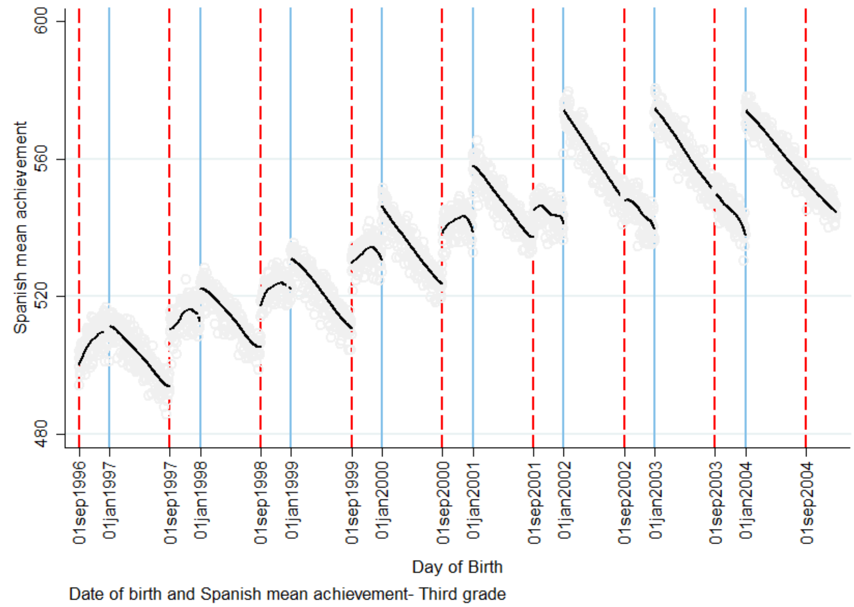

Figure 4.9: Average Spanish performance by date of birth. Source:Author's calculation using ENLACE

4.6.2 Results Reform

Table 4.13 shows the results from the education production function (equation 4.8) for each set of cutoffs. Employing six (intra birth cohort-age effect) estimates (six sets of cutoffs) of the causal effect by birth cohort and subgroups, these estimates are interpreted as local average treatment effects for those born near cut-off dates and who delayed their enrollment. For those students of varying ages across the cut-off who were born in 1998-1999 and therefore enrolled before the school entry reform, the age effect is significant and about 50 points in ENLACE (0.5 s.d.) including controls which give more precision to the estimator. This effect does not change across gender or using various specifications. Following the results of Elder and Lubotsky (2009), differences in age are more pronounced for students coming from families with greater socioeconomic background. In addition, private schools have a greater age effect than public schools by 0.09 s.d. For this cohort, those who delayed enrollment and attended school in the following year performed in the standardized test half of a standard deviation greater than those who attended school younger and entered school in a previous school year. The great magnitude of this coefficient is important;

attending a school year in 2008-2009 instead of the school year 2007-2008 (a year older) increased math achievement by 50 points in ENLACE. It is worth to recall that this effect includes the direct effect of age (age at the test and entry age) plus those indirect effects of age in parental and school inputs since they entered the first grade.

Table 4.13: The Effect of Age on Math Achievement over time, intra-age

		Without controls	Controls	Female	Male	Public	Private	Quadratic
1998-1999	Age	49.2***	49.5***	49.3***	49.8***	49.5***	58.5***	47.9***
	S.E.	3.041	2.988	3.999	4.381	3.046	9.233	4.017
	$\bar{Age}$	8.1***	8.1***	9.1***	8.3***	1.2***	7.0	10.2***
	S.E.	2.443	2.376	3.138	3.468	2.397	7.993	3.396
	Obs	1283291	1258635	616758	641877	1103420	110432	1258635
1999-2000	Age	59.17***	59.34***	56.21***	62.46***	61.23***	59.36***	59.72***
	S.E.	1.27	1.27	1.63	1.80	1.30	4.48	1.35
	$\bar{Age}$	-0.04	-0.12	3.98***	-2.84***	-7.51***	10.25***	-0.97
	S.E.	1.16	1.17	1.50	1.65	1.20	4.04	1.53
	Obs	1344999	1321202	649344	671858	1152306	115281	1321202
2000-2001	Age	54.30***	54.78***	57.75***	51.59***	55.35***	49.43***	53.93***
	S.E.	1.37	1.38	1.80	1.89	1.42	4.37	1.52
	$\bar{Age}$	5.30***	5.05***	4.14***	7.51***	-2.22**	18.17***	6.97***
	S.E.	1.24	1.25	1.64	1.72	1.29	3.87	1.64
	Obs	1372479	1351028	665159	685869	1178072	119313	1351028
2001-2002	Age	61.12***	61.20***	60.58***	61.76***	63.24***	54.23***	60.24***
	S.E.	1.17	1.17	1.52	1.63	1.21	4.13	1.45
	$\bar{Age}$	-0.04	0.38	2.37	-0.10	-6.79***	12.66***	1.37
	S.E.	1.23	1.24	1.63	1.72	1.28	4.02	1.72
	Obs	1350181	1329981	655828	674153	1159620	117918	1329981
2002-2003	Age	80.35***	80.56***	82.07***	78.96***	80.98***	75.15***	82.75***
	S.E.	1.09	1.09	1.44	1.55	1.13	4.21	1.59
	$\bar{Age}$	-20.06***	-18.91***	-19.38***	-17.05***	-23.00***	-7.04	-19.59***
	S.E.	1.29	1.31	1.73	1.84	1.35	4.58	1.92
	Obs	1307446	1287827	638087	649740	1123997	116771	1287827
2003-2004	Age	79.97***	79.93***	81.36***	78.36***	80.03***	80.72***	79.88***
	S.E.	1.09	1.09	1.44	1.55	1.14	3.93	1.59
	$\bar{Age}$	-21.56***	-20.58***	-21.15***	-18.60***	-23.67***	-11.57***	-0.18 ***
	S.E.	1.31	1.34	1.78	1.87	1.39	4.50	0.02
	Obs	1191252	1174592	584278	590314	1023703	113540	1174592

Source: Author's calculations using ENLACE (2006-213)
SE are clustered at the school level.

For the 1999 and 2000 cohorts, the first generation that started school under the 2006 reform, the age effect is 59 points in ENLACE (0.59 s.d.). That is, the 2006 reform had a short-run effect on student achievement. There are several channels that these cohorts were impacted by the reform, 1)an increase in class size, 2) a relative increase of younger students , and 3) uniformity among states, who started their transition to one, federal cutoff. The reforms affected males more than females, and students in public schools more than those in private schools. For the 2000 and 2001 cohorts, the age effect was again significant and of a considerable magnitude. After these cohorts (for older generations), the age effect increased. For those born around the cutoffs date in 2001-2002, the age effect is 0.61 s.d.; whereas for those 2002-2003, the age effect is 0.8 s.d. Finally, for the latest cohorts, 2003 and 2004, the age effect is 0.8 s.d. which is 0.03 s.d. higher for females than for boys. Generally speaking, the inclusion of covariates does not affect the stability of the parameters estimated nor the nonlinear form of the EPF.

Looking at the impact of peer effects: the coefficient on average age varies significantly over time, being negative for cohorts entering first grade before the 2006 reform and becoming highly positive and significant for later cohorts. For the 1998-99 cohort, for example, (which is before the reform)the coefficient of average age is 8 points of ENLACE (0.08 s.d.); recalling Elder and Lubotsky (2009), the coefficient of the average age has an implicit negative sign (according with equation 4.10, $\beta_2 = -\alpha_2$); that is, students who delayed enrollment (due to the cutoff and the date of birth) had a negative effect to be older with respect to the average age in class [4]. But for the 2002-2003 cohort, the average age of the class for those who delayed enrollment has a positive and significant impact on math achievement. This suggests that, over time, the incentives for delayed enrollment may have risen as a result of the 2006 law: with younger average ages, students who delay their entry into school would be entering even younger peers and the lower average age would have a strong positive effect on the tests scores of the older, age-delayed students. This effect is stronger for students in public schools, relative to private schools.

The analysis in this dissertation also finds that the 2006 reform reduced the variance of the age

[4] Elder and Lubotsky (2009) mention “note that a positive effect of the school average entrance age corresponds to a negative effect of a child’s age relative to the school average” p. 668

distribution in the ENLACE population. Figure 4.10 illustrates this point.

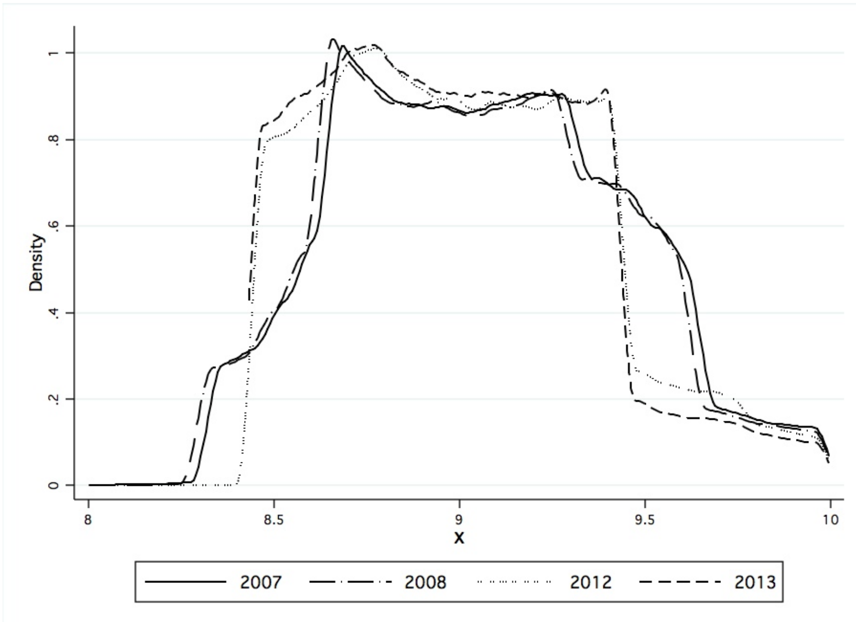

Figure 4.10: Density of the Average Age at the Test by School Year. Source:Author's calculation using ENLACE

Table 4.14 shows the estimates for those who attend the same school year and grade but differ on the year of birth. For those who attend third grade in 2012, the age effect is positive and equal to 0.52 s.d. or approximately 52 points in the equation with controls. There is a slight difference in the coefficient on the basis of gender, with a difference of 1.5 points between females and males. In addition, there is also variation on the basis of the type of school, with the inter-age effect for students in public schools equal to 0.52 s.d., whereas for students in private schools it is 0.60 s.d. The estimates presented in this Table show that the coefficient of the average classroom grade on student achievement is positive. This means that a child who delays enrollment, and whose classroom peers would be younger, would face a negative impact of about seven points on math student achievement through the peer effect. This impact of the age of peers on student achievement is stronger among private school students.

Table 4.14: The Effect of Age at the test on Math Achievement inter-age, school year 2011/2012 and 2012/2013

		Without controls	Controls	Female	Male	Public	Private
2012	Age	50.57	51.48	52.92	49.93	51.82	59.98
	S.E.	1.05	1.04	1.42	1.53	1.07	3.77
	Average Age	7.85	7.31	8.12	8.23	3.06	7.17
	S.E.	1.08	1.13	1.49	1.61	1.16	3.93
	Observations	1912301	1883412	925047	958365	1638672	179140
2103	Age	52.32	52.85	53.52	52.05	53.05	63.27
	S.E.	1.01	1.01	1.36	1.48	1.05	3.77
	Average Age	8.89	7.57	8.64	8.36	3.97	7.77
	S.E.	1.05	1.10	1.45	1.56	1.13	3.85
	Observations	1863887	1836546	900461	936085	1595513	171850

Source: Author's calculations using ENLACE (2006-213)
SE are clustered at the school level.

Table 4.20 (this later in the annex) shows the estimates for those in the same grade and the same birth cohort but different school year. In contrast, Table 4.15 shows the estimates for those in the same grade and the same school year but different birth cohort. The comparison here involves the test scores of the older, school-delayed students in third grade with those of the younger students in the same grade (who entered on time) in the given school year. The (inter)-age effect is very similar to the (intra)-age effect (see table 4.11 for these definitions). However, before the reform the inter-age effect was larger than the intra-age effect, after the reform and transition, it is the opposite story. This difference may be associated with the fact that more recent generations taking the ENLACE tests have increased achievement tremendously, thus postponing enrollment may imply better "education" in the subsequent school year. However, this may also be the result from other opportunistic behaviors of school actors (e.g. cheating), which may be rising over time. Table 4.15 depicts that the age effect is 64 points in ENLACE for those who were born around September 1, 1998. This effect decreased after the implementation of the reform; for example those who attend third grade in 2012 and were affected by the cutoff, the age effect was 55 points of ENLACE.

In conclusion, regardless of the sample, the school year or birth cohort, the age effect estimated in this dissertation is equal to about a half standard deviation, suggesting that age has a significant, positive impact on student achievement. While the age effect for those in the same birth cohort has

Table 4.15: The Effect of Age on Math Achievement over time, inter-cohort

	Coeff	S.E.	Obs
Sep 1 1998	62.04	0.95	656591
Sep 1 1999	60.20	1.22	535545
Jan 1 2001	64.20	0.44	550049
Jan 1 2002	57.13	0.33	879971
Jan 1 2003	52.11	0.32	1222939
Jan 1 2004	54.96	0.33	1191252

Source: Author's calculations using ENLACE
SE are clustered at the school level.

increased over time and in particular after the 2006 reform, the age effect has decreased over time for those who attend the same school year. This result suggest that the age effect may be capturing other factors that have positively affected the education production function in more recent school years.

4.6.3 Threats to validity

Regression discontinuity designs have several limitations and present potential threats to quasi-experimental studies. In order to test the validity of the regression discontinuity design, the current study first determines whether the distribution is continuous at September 1, tests for discontinuities in covariates not related to the treatment at the cut-off, and then tests for discontinuities at non-discontinuity points. (Recall how Bound and Jaeger (2000) found some evidence of small differences in health across seasons of birth—differences, for example, between winter- and summer-born children.)

Furthermore, state cut-off dates may be endogenous and respond to decisions regarding school inputs and correlated with the average characteristics of children in a state. While major school inputs are developed or delivered by the federal Ministry of Education (e.g., curriculum, text books, school calendar, etc.) and federal education funds are formulated with the same unit cost for everyone, states can add more resources, and states with younger average cohorts may provide more or less school resources. After the 2006 reform, all states finally adhered to the same cut-off date—a fact reflected in Figures 4.15 and 4.14 in the Annex.

Histogram tests can also reveal manipulation of assignment variables. If the distribution of data at a cut-off point is continuous, the data implies that no manipulation of the assignment variable occurred. By contrast, if, for example, parents were successful at "scheduling" birth dates relative to a specific cut-off date, the distribution of births would tend to stack around that cut-off date. Figure 4.11 presented a histogram of Mexican birth dates whereby September 1 births do indeed out-number September 2 births—evidence that parents successfully engaged in some sort of birth date manipulation vis-à-vis a cut-off date.

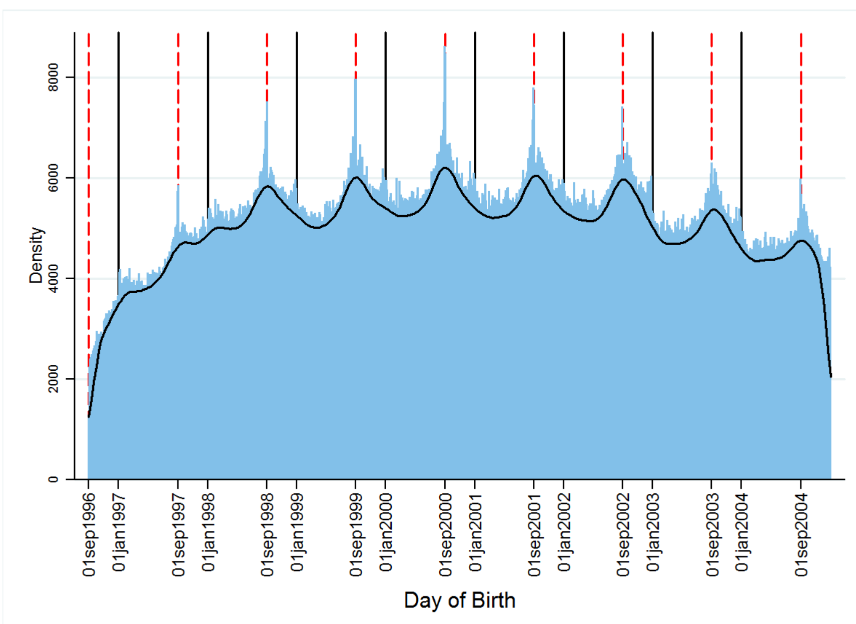

Figure 4.11: Histogram of the number of Individuals by date of Birth. Source:Author's calculation using ENLACE

Stacking alone, however, does not necessarily violate assumptions required for regression discontinuity. As Urquiola and Verhoogen (2009) emphasize, " The violation of the regression discontinuity assumption arises from the interaction of the stacking and the endogenous sorting of households

". To test if the quasi-experimental assignment is random at a cut-off, the continuous density of the data points was tested. Table 4.16 showed the results of a McCrary test—a measurement detecting changes in the density distribution of an assignment variable. The results of the McCrary test indicated the assignment variable was subject to non-random manipulation. In particular, the McCrary test showed an estimated discontinuity of -0.13 or -13% more observations on the left side of the 1998 cut-off, with a standard error of .004. Moreover, January 1 produced more discontinuities across all cut-offs with a maximum of 27% more births after a cut-off and a minimum of 5 percent. With results like these, the null hypothesis of continuity can be rejected.

The McCrary (2008) test on the assignment variable (Day of birth) results in an estimated discontinuity of $-.0117$, with a standard error of .005. Therefore, the null hypothesis of continuity is not rejected.

Table 4.16: McCrary density test

	Cutoff	Discontinuity estimate (log difference in height)	S.E.
1998	1-Sep	-0.13	(.004)
	1-Oct	0.02	(.004)
	1-Nov	0.06	(.004)
1999	1-Jan	0.24	(.004)
	1-Sep	-0.09	(.004)
	1-Oct	0.00	(.004)
	1-Nov	0.00	(.004)
2000	1-Jan	0.05	(.004)
	1-Sep	-0.10	(.004)
	1-Oct	0.01	(.004)
	1-Nov	0.08	(.004)
2001	1-Jan	0.23	(.004)
	1-Sep	-0.1	(.004)
	1-Oct	0.02	(.004)
	1-Nov	0.05	(.004)
2002	1-Jan	0.27	(.003)
	1-Sep	-0.05	(.004)
	1-Oct	0.05	(.005)
	1-Nov	0.05	(.004)
2003	1-Jan	0.18	(.003)
	1-Sep	-0.06	(.004)
	1-Oct	0.03	(.005)
	1-Nov	0.05	(.005)
2004	1-Jan	0.19	(.004)

Source: Author's calculations.

Finally, in order to assess the plausibility of the identification strategy, the analysis tested discontinuities at September 1 via factors which are orthogonal to 1st grade entry ages. If, for example, student characteristics vary sharply near September 1, the identification strategy itself is undermined.

Looking at some possible discontinuities, Figure 4.12 illustrated the mean values of schooling of the mother by date of birth. The relationship between education and day of birth is flat over 365 days.

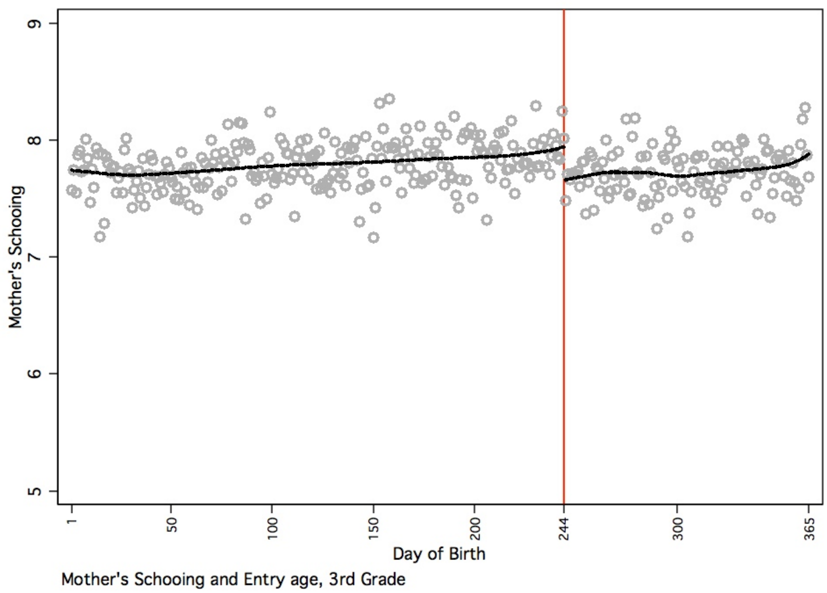

Figure 4.12: Average Mothers' Schooling by day of birth in 2008

4.7 Conclusion

This research has analyzed the impact of age on student achievement in México. In order to more accurately evaluate the effects of age on achievement, the study exploited two different identification strategies: exogenous variation in education vis-à-vis dates of birth and the school entry age reform law of 2006. In 2006, a new school entry age law was passed in México which reduced the minimum age to enter academic schooling by four months. This reform had two observable effects: It lowered both the average entry age of 1st grade students and the relative homogeneity of the school-entry ages among 1st grade students. Before the 2006 reform, most Mexican states used September 1 as their cut-off-date; after the reform, states transitioned to December 31. Due to the

2006 law, some children were allowed to begin school earlier than was permitted in prior years. To estimate the potential effects of these variables on math scores, a fuzzy regression discontinuity was used to track the causal effect of delayed school enrollment on student outcomes whereby the source of identification was age at test variation.

The results indicate that older students generally scored higher than younger students. In addition, the reform impacted this result, with the gap between those regulated by the new cut-off dates and those regulated by the old cut-off date(s) equal to 0.30 s.d. (comparing the 1998-1999 cohort with 2002-2003 cohort). This result suggests that the age effects on schooling outcomes is stronger for the more recent generations when compared to cohorts in school previous to the reform. While there is an increased age effect after the reform, one possibility is that school inputs were not adjusted to younger students (e.g. curriculum, etc), even when these new generations were more prepared before first grade (compulsory kindergarten). Because math scores have increased by 0.95 s.d. since the first administration of ENLACE in 2006, this result suggests that, at a minimum, moving the cut-off date by four months to December 31 did not have an adverse effect on mean math test scores.

Because entry-age dates affect class composition, peers effects have changed due to the 2006 reform. Students in the 1998-1999 cohort (who entered school prior to the reform) who delayed school and attended a class composed, on average, being the older students, scored lower (negative effect) by 0.08 s.d. By contrast, the same effect after the 2006 reform was estimated to be positive at 0.22 s.d.

Although age appears to have a strong effect on student achievement throughout the various analyses in this dissertation, there is a difference in results obtained from the intra-age cohort analysis versus the inter-age cohort analysis. The intra-age analysis compares the outcomes in third grade of students who were born in the same cohort but because they were slightly younger or older they ended up entering first grade with one year of difference. The inter-age analysis also maintains the grade constant, but compares the older students who delayed enrollment due to the law with the younger students in the same school year, with the two groups belonging to two different birth cohorts. In this case, the comparison was between the outcomes of the older, school-delayed students in third grade with those of the younger students in that same grade (who entered on-time) in a given school year.

First, the intra-age effect of delaying 1st grade by a year on math scores was an increase of 0.5 s.d. For the generations prior to the reform attending 3rd grade, the inter-age effect of delaying 1st grade by a year on math scores was an increase of 0.62 s.d. That is, the intra-age counterfactual provided estimates of age on math achievement which were higher than the inter-age counterfactual. On the other hand, after the school reform of 2006 (looking at the 2003-2004 age cohort), the results obtained from the intra-age strategy imply that delaying 1st grade by a year on math scores yielded an increase of 0.8 s.d., while the inter-age estimation strategy implied that the effect of delaying 1st grade by a year on math scores was an increase of 0.53 s.d. In other words, the intra-age counterfactual produced estimates of age on math achievement that were stronger than the inter-age strategy.

Underlying the results of this research is the fact that there has been a large increase in test scores over time in México. The impact of age on schooling, specially the changes over time in the rate of return to age in terms of student achievement, may be connected to this trend. This requires further research as it involves analyzing the changes in resources and choices made by schools, teachers and parents over time, which may be impacting test scores (including the pre-schooling and other reforms implemented by the government as well as the possibility of increased cheating or teaching to the test, among many other factors). Indeed, there are many limitations to the age-effect analysis carried out in this dissertation. First, the estimated age effect aggregates several effects which are dependent upon age and includes not just the impact of maturation –which makes older students do better in test scores—but also any greater investments made by parents in their children during the extra time connected to the delay of entry into first grade. Second, since test scores are not comparable across grades, it is not possible to estimate the schooling effect (as described in the chapter's theory section). Third, there is some evidence of birth manipulation among parents. Though this manipulation may not invalidate the identification strategy (especially if before the reform, the percentage of students who had accelerated school entry equaled the percentage of students who had delayed enrollment), it can cause an underestimation of the age effect. Fourth, the kindergarten reform that occurred in parallel to the 2006 age-entry reform may be one of the reasons math scores increased over time. However, the age effect cannot be disentangled from this effect across birth cohorts. Finally, a 2010 teachers incentive program may have induced strategic behaviors among teachers and principals (e.g., systematic cheating or teaching to the test) which can distort the estimation of the intra-age effect.

Though the current research focused on the effect that delayed enrollment may have on student achievement, there are other issues to consider. One important issue relates to age dispersion. What is the optimal mix of student ages in a classroom? This issue deserves its own research agenda.

Policy recommendations. Before the entry-age reform of 2006, some states systematically allowed younger children to enroll in 1st grade, and thus, had lower average ages in their classrooms. Several published analyses did not account for these state-by-state differences, yet we know that states with older students score, on average, 8 points higher in ENLACE exams respect to lower average age classes. These results demonstrate that systematic de jure or de facto rules which influence classroom composition may lead to differences in average test scores across Mexican states. Moreover, this result also suggests that comparing schools which have more discretion in the selection of students (e.g., private schools) with those that don't (e.g., public schools)must be carefully considered in terms of their impact on the average age of students and its connection to relative student achievement. Nevertheless, because national enrollment reform generally increased classroom homogeneity throughout México, comparisons among Mexican states are more accurate than before the reform.

Another issue to consider is that Mexican authorities have recently begun to enforce a "no-failing" policy for the first three grades of school. While several critics have raised concerns, the fact that the estimated age effect is above 0.5 s.d. demonstrates that younger children are at a disadvantage relative to those who delay school entry even if both groups have increased their performance over time. Because failing is actually correlated with entry age during the first three grades of school, this "no-failing" policy promotes these younger students to an upper grade, but does not address the disadvantages of younger students.

México has addressed many problems related to educational access, especially since the 2006 reform. Two complications, though, have arisen from these successes: greater human capital heterogeneity and greater age heterogeneity among all the children entering the 1st grade (due to overage enrollment). Whereas compulsory kindergarten can help to mitigate the first problem, a nationally uniform entry-age policy would have presumably resulted in more homogenous classrooms. So while underage enrollment is no longer much of an issue, overage children are a problem related to socioeconomic status, migration (temporal and permanent) patterns and access. The intra-cohort peer effects estimated in this dissertation suggest that that children should transit the school system with children of the same age.

The results of this dissertation regarding school entry-age reform also illustrates that administrative and legislative decisions have an impact on classroom compositions (both in increased age diversity and increased size) which in turn affect teaching and learning outcomes.

In conclusion, what, then, is known about the best time to start school? Is it merely a question whether or not younger entrants gain more or less from schooling than older entrants? The impact of age on student achievement estimated in this dissertation is positive and significant (regardless the sample, the school year or birth cohort, the effect of school delay is half a standard deviation or above). This result, which is the outcome of the greater maturity as well as greater parental inputs obtained by being one year older when you enter school, suggests that it is better to be the head of the mouse than the tail of the lion in México. But this result claim for better classroom composition or organization, and does not support red shirting. However, it should also be emphasized that when a sizable portion of the student population delays enrollment, there are consequences on both students and the school system that are not measured by the impact of age on individual student outcomes examined in this dissertation. An examination of these impacts should be the task of future research.

4.7.1 Tables

Table 4.17: ENLACE - census-based assessment - Official numbers

	Third	Fourth	Fifth	Sixth	7th	8th	9th	Total
2006	1,840,417	1,892,833	1,909,516	1,863,489	—	—	1,371,202	8,877,457
2007	1,984,594	1,955,348	2,038,536	1,984,347	—	—	1,526,867	9,489,692
2008	2,009,201	2,042,002	2,030,916	2,026,575	—	—	1,614,281	9,722,975
2009	2,081,460	1,946,074	1,908,484	1,874,055	1,732,862	1,682,712	1,582,315	12,807,962
2010	2,224,353	2,140,003	1,977,389	1,981,983	1,820,767	1,747,413	1,642,129	13,534,037
2011	2,264,175	2,231,429	2,135,273	2,000,214	1,849,676	1,729,023	1,636,471	13,846,261
2012	1,979,766	2,099,700	2,055,989	2,006,188	1,801,856	1,702,920	1,575,028	13,221,447

Source: Author's calculations using ENLACE
Official numbers from SEP.

Table 4.18: Birth cohorts and ENLACE cohorts

	1997	1998	1999	2000	2001	2002	2003	2004
Total Births	2,285,050	2,296,222	2,350,401	2,411,271	2,285,777	2,185,073	2,097,139	2,034,460
Michoacán	102,642	102,231	103,937	105,982	99,135	91,367	85,321	80,840
Oaxaca	84,701	84,856	86,377	88,259	83,814	78,642	74,670	71,772
Aguascalientes	24,010	24,414	25,199	26,033	25,324	24,343	23,714	23,297
Colima	11,422	11,534	11,835	12,173	11,637	11,008	10,567	10,264
No Oax & Micho	2,097,707	2,109,135	2,160,087	2,217,030	2,102,828	2,015,064	1,937,148	1,881,848
ENLACE	1458501	1946236	1981753	2053835	2018067	1992465	1799251	1628048
Oaxaca	14,526	38,707	44,970	5,632	27	41	98	714
Michoacán	20,369	36,965	5,146	30,272	33,178	35,513	17,194	20,862
Colima	10,654	11,110	11,130	11,678	11,210	11,428	10,908	8,245
Aguascalientes	23,028	23,688	24,073	25,268	25,040	25,109	24,026	20,739
Total	63.8%	84.8%	84.3%	85.2%	88.3%	91.2%	85.8%	80.0%
No Oax & Micho	67.9%	88.7%	89.4%	91.0%	94.4%	97.1%	92.0%	85.4%
Oaxaca	17.1%	45.6%	52.1%	6.4%	0.0%	0.1%	0.1%	1.0%
Michoacán	19.8%	36.2%	5.0%	28.6%	33.5%	38%	20.2%	25.8%
Aguascalientes	95.9%	97.0%	95.5%	97.1%	98.9%	103.1%	101.3%	89.0%
Colima	93.3%	96.3%	94.0%	95.9%	96.3%	103.8%	103.2%	80.3%

Source: Author's calculations using ENLACE

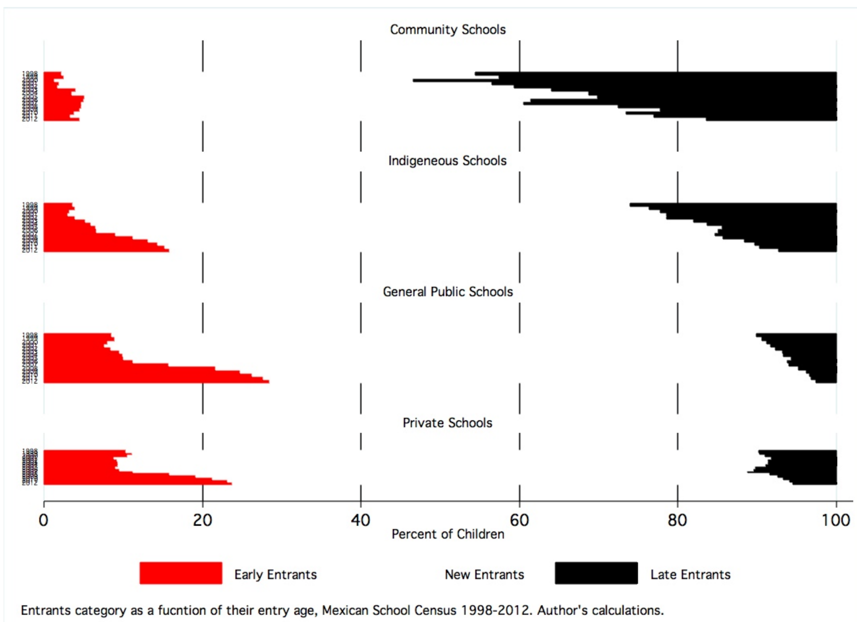

Figure 4.13: Enrollment by Entrants category in First Grade. Source:Author's calculation using 911 data

Table 4.19: Marginality and Late age students in third grade

	Very Low		Low		Medium		High		Very High	
	Public	Private	Public	Private	Public	Private	Public	Private	Public	Private
2006	0.07	0.08	0.08	0.12	0.11	0.11	0.14	0.10	0.20	0.02
2007	0.11	0.09	0.11	0.12	0.16	0.10	0.18	0.10	0.17	0.03
2008	0.11	0.10	0.11	0.12	0.16	0.12	0.19	0.10	0.19	0.02
2009	0.10	0.09	0.10	0.11	0.15	0.09	0.18	0.10	0.17	0.01
2010	0.30	0.31	0.26	0.27	0.33	0.28	0.33	0.18	0.28	0.05
2011	0.23	0.25	0.19	0.23	0.26	0.21	0.27	0.16	0.25	0.05
2012	0.15	0.18	0.14	0.19	0.19	0.17	0.21	0.16	0.21	0.05
2013	0.12	0.14	0.11	0.16	0.15	0.14	0.18	0.13	0.19	0.04

Source: Author's calculations using ENLACE

Table 4.20: The Effect of Age on Math Achievement over time

		No controls	Controls	Female	Male	Public	Private	Quadratic
1998-1999	Coeff	58.5	58.9	59.9	59.4	50.7	66.5	58.4
	S.E.	0.839	0.889	1.193	1.214	0.906	2.187	1.184
	Obs	1283291	1258635	616758	641877	1103420	110432	1258635
1999-2000	Coeff	59.1	59.2	59.6	59.9	54.8	69.3	59.1
	S.E.	0.731	0.763	1.005	1.048	0.805	2.072	0.879
	Obs	1344999	1321202	649344	671858	1152306	115281	1321202
2000-2001	Coeff	59.20	59.36	61.48	58.46	53.36	66.91	58.82
	S.E.	0.722	0.761	1.010	1.041	0.795	2.130	0.917
	Obs	1372479	1351028	665159	685869	1178072	119313	1351028
2001-2002	Coeff	61.09	61.49	62.35	61.68	58.17	65.56	61.10
	S.E.	0.645	0.674	0.885	0.928	0.700	2.123	0.871
	Obs	1350181	1329981	655828	674153	1159620	117918	1329981
2002-2003	Coeff	65.47	66.87	68.26	66.37	64.55	69.25	68.53
	S.E.	0.552	0.587	0.761	0.786	0.613	1.864	0.802
	Obs	1307446	1287827	638087	649740	1123997	116771	1287827
2003-2004	Coeff	64.76	65.88	67.15	65.42	64.10	71.78	66.60
	S.E.	0.567	0.608	0.816	0.837	0.643	1.862	0.884
	Obs	1191252	1174592	584278	590314	1023703	113540	1174592

Source: Author's calculations using ENLACE
SE are clustered at the school level.

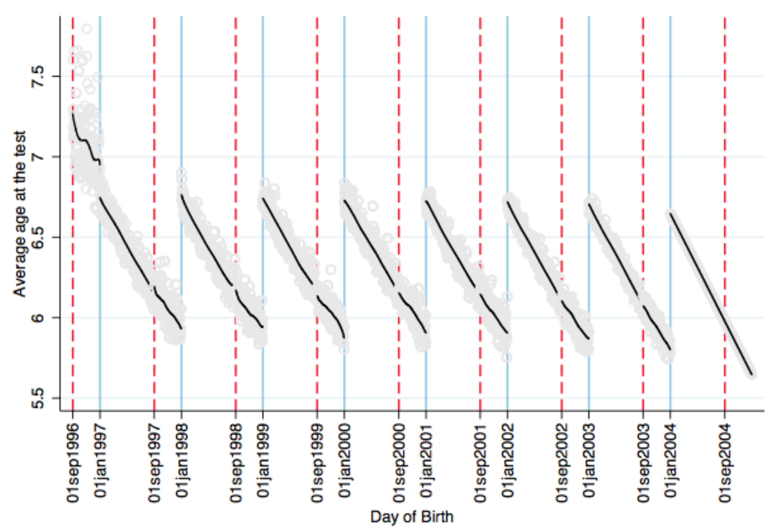

Figure 1. Date of birth and average entry age – Third grade, estado 1

Figure 4.14: First state, Aguascalientes. Source:Author's calculation using ENLACE

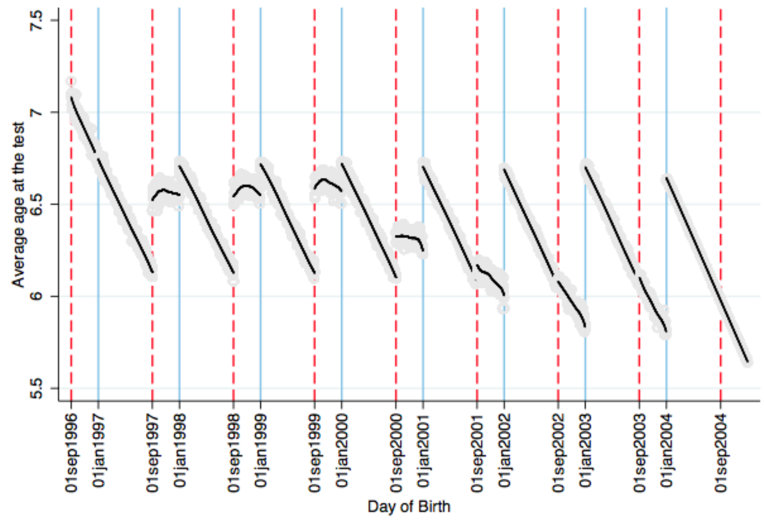

Figure 1. Date of birth and average entry age – Third grade, estado 9

Figure 4.15: First state, D.F. Source:Author's calculation using ENLACE

Simple Theoretical model

The Entry – Age Effect. A further theoretical perspective on the entry-age effect (as defined here) was contributed by Elder and Lubotsky (2009). These authors discussed how the relationships between family inputs and test scores change as a response to changes in entry-age. Elder and Lubotsky (2009) argue that the accumulation of knowledge prior to the start of kindergarten explains the gap between the oldest and youngest entrants and within each group of rich and poor students. Datar (2006) argues that activities prior to school may affect the impact of age on test scores when a child is in school. Following the previous notation, the theoretical model of Elder and Lubotsky (2009) is:

$$\mathbf{T_{ia}} = \mathbf{T_a}(\mathbf{T_{i,EA}}, \mathbf{F_{age}}, \theta_{\mathbf{i,SA}}(\mathbf{S}, \mathbf{EA})) \tag{4.11}$$

$\mathbf{T_{i,EA}}$ is the cognitive achievement of an individual previous to school (human capital in the theoretical model of Elder and Lubotsky (2009)). $\theta_{\mathbf{SA}}(\mathbf{S}, \mathbf{EA})$ is the contribution of a year $\mathbf{S}$ of schooling to the human capital of a child who entered school at age $\mathbf{EA}$. According to this model, an individual who starts school at $\mathbf{EA = t}$ has an evidently lower cognitive starting point than the same individual starting school a year older ($\mathbf{EA = t+1}$). In fact, the accumulated parental inputs will be higher for the older individual than for the younger one. On the first day of kindergarten, a child's human capital consists only of previous parental investments and is given by:

$$\sum_{\mathbf{j=0}}^{\mathbf{EA=age}} \beta^{\mathbf{j}} \mathbf{F_{EA-j}} = \mathbf{T_{EA=age}} < \mathbf{T_{EA=age+1}} = \sum_{\mathbf{j=0}}^{\mathbf{EA=age+1}} \beta^{\mathbf{j}} \mathbf{F_{EA-j}} \tag{4.12}$$

Elder and Lubotsky (2009) claim that differences in test scores at the moment children begin school are explained by the effect of a year of parental resources through differences in age. Consequently, and extra year of parental inputs creates heterogeneity among new entrants of different ages. Note, however, that following Equation 4.12, these authors do not explain the complete entry-age effect (which includes direct and indirect effects). That is, Elder and Lubotsky (2009) contributed to the discussion by focusing on the effect of entry-age on family inputs, but did not incorporate the entry-age direct effect on test scores (the ceteris paribus effect). Finally, the authors argue that student achievement among the richest new entrants will be higher than among the poorest entrants due to the capability of rich families to provide higher parental investments during that extra year.

The School – Age Effect. Furthermore, while the entry-age effect is clearly defined by two components, age and family inputs, the total school-age effect is not clearly defined due to the perfectly collinear relationship between current age and accumulated schooling among on-track children(Angrist and Pischke, 2008; Elder and Lubotsky, 2009; Fredriksson and Öckert, 2005; Datar, 2006). That is, while children are in school, an extra year out of formal school affects not only their cognitive achievement on tests through mental capacity (age) but also affects their accumulated experience in the form of parental and school inputs. Moreover, this model can be extended by adding two types of school inputs in order to understand the effect of school age on the cognitive achievement model. Assuming there are two types of inputs, a fixed school input is the school-grade in which the student is eligible to enroll, and the adaptive school input includes the resources devoted to the student during that school year. For example, school grades typically have defined curriculum standards whereas there are no rules determine hours of tutoring by grade. In this approach, the school-age effect can be divided using these two school inputs. The total effect of school age on the cognitive achievement model is expressed as:

$$\frac{\delta \mathbf{T_{ija}}}{\delta \mathbf{SA}} = \frac{\delta \mathbf{T_{ija}}}{\delta \mathbf{SA}} + \frac{\delta \mathbf{T_{ija}}}{\delta \mathbf{F_{ij}}} \frac{\delta \mathbf{F_{ij}}}{\delta \mathbf{G}} \frac{\delta \mathbf{G_i}}{\delta \mathbf{SA}} + \frac{\delta \mathbf{T_{ija}}}{\delta \mathbf{G_{ij}}} \frac{\delta \mathbf{G_{ij}}}{\delta \mathbf{SA}} + \frac{\delta \mathbf{T_{ija}}}{\delta \mathbf{F_{ij}}} \frac{\delta \mathbf{F_{ij}}}{\delta \mathbf{ASI}} \frac{\delta \mathbf{ASI_i}}{\delta \mathbf{SA}} + \frac{\delta \mathbf{T_{ija}}}{\delta \mathbf{ASI_{ij}}} \frac{\delta \mathbf{ASI_{ij}}}{\delta \mathbf{SA}} \tag{4.13}$$

The first component is the age-at-test effect on cognitive achievement. The second component is the effect of family inputs on cognitive achievement conditional to attending a lower grade (G=grade). The third component is the effect of a lower grade on achievement due to delayed enrollment by one year. This effect is negative due to students losing one year of schooling. The following component is the effect of family inputs on test scores as a result of changes in the adaptive school inputs of a child one year older. The last component is the effect of the adaptive school inputs on cognitive achievement as a consequence of delayed enrollment. In this extension, delayed enrollment automatically results in attending a lower grade than if they had entered the previous year. Starting a year older is a balance between the cognitive return of an extra year before school and the cognitive return of another year of schooling. Consequently, the school-age effect has three defined effects, 1) the age-test effect, 2) the age-grade-effect, and 3) the age-adaptive school input effect, where the last two can be considered the schooling effect.

The Age – Grade Effect. In the literature on the short-term effects of age, a debate emerges regarding counterfactuals, related to delayed enrollment. For example, Datar (2006) mentions that " When examining short-term outcomes such as test scores in school, one key issue relates to the point at which these children should be compared, i.e., in the same grade or at the same age " (p.45). Individuals face a tradeoff between age and schooling, entering one-year-older means postponing academic instruction by one year and spending a year of activities out of school. While there are two direct effects of age on cognitive achievement relative to entry-school age, the EPF adjusts family and school inputs accordingly. In other words, whereas most of the research on this topic seeks to disentangle the direct effects of age (entry-age and age-at-test-effects), the model used by Todd and Wolpin (2003) uses non-ceteris paribus mechanisms by which age impacts cognitive achievement.

Theoretically, the age-grade effect is similar to a years-of-schooling effect. Suppose one could compare the effect of schooling of an individual $\mathbf{i}$ in a year of schooling $(\mathbf{S})$ with the same individual in a year of schooling $(\mathbf{S-1})$ at the same age. (These types of counterfactuals are obviously not possible, and are considered a fundamental problem regarding causal inference). For illustration, the treatment effect for this hypothetical individual is the difference in outcomes due to the effect of the fixed school input (the grade). This effect can be called "the treatment of the treated schooling effect" $\mathbf{g}$ instead of grade $\mathbf{g-1}$.

$$\left[\mathbf{T_{i,t=age}}|\mathbf{S=g}\right]-\left[\mathbf{T_{i,t=age}}|\mathbf{S=g-1}\right] \tag{4.14}$$

Following the model used by Todd and Wolpin (2003) , the effect of being in a higher grade is:

$$\frac{\delta \mathbf{T_{ija}}}{\delta \mathbf{S_{ij}(SA)}}=\frac{\delta \mathbf{T_{ija}}}{\delta \mathbf{F_{ij}}}\frac{\delta \mathbf{F_{ij}}}{\delta \mathbf{G}}\frac{\delta \mathbf{G_{i}}}{\delta \mathbf{SA}}+\frac{\delta \mathbf{T_{ija}}}{\delta \mathbf{G_{ij}}}\frac{\delta \mathbf{G_{ij}}}{\delta \mathbf{SA}} \tag{4.15}$$

Equation 4.13 is equal to the age-grade component in Equation 4.15. Moreover, a similar approach was developed by Cahan and Cohen (1989). This study discussed the age-at-test effect and the schooling effect of entering a year older relative to academic instruction. That is, the absolute effect of an additional year of schooling on achievement can be estimated by holding age constant (given age is the only factor of admission in school). This effect can be estimated as a " treatment on the treated." These authors argue that " the difference between any two adjacent grade levels in mean achievement can be viewed as the sum of the effects of two factors: one year of schooling and an average of one year in chronological age. In order to isolate the independent effect of one year of schooling, one has to partial out the independent effect of one-year difference in chronological age" (p. 3). In other words, the effect of schooling on cognitive achievement is driven by:

Table 4.21: Net Enrollment-Age Effect of Being Older, Shown by the model by Cahan and Cohen (1989)

	Age-effect	Schooling-effect
Treatment	Age t, grade x	Age t, grade x
Control	Age $t-1$, grade x	Age t, grade $x+1$

The authors define the age effect as the differences in the mean test scores between individuals with one year differences in chronological age in the same grade and the schooling effect as the difference in mean test scores between individuals of one year of schooling difference born around the entry-school day between two consecutive grades. Maintaining the grade constant, this strategy compares the oldest students who delayed enrollment age due to the law with the youngest students who were born around the entry-date of formal education. The only difference is one year in age. Maintaining the age constant, the strategy compares the oldest students who delayed enrollment age due to the law with the youngest students who are in the next grade. The same achievement test is needed to compare individuals of the same age but in different grades (Cahan and Cohen, 1989). In this theoretical model, the school effect exists as the total age-grade effect that is part of the total school-age effect.

4.7.2 Extension of Todd and Wolpin (2003)

Consider a simple cognitive achievement model in which the education production function is a cumulative process where each level of achievement is prerequisite for subsequent learning. This cognitive production function follows partially Elder and Lubotsky (2009) model and it can be considered an extension of the cognitive production function developed by Todd and Wolpin (2003). The importance of this extension is to define a structure of the EPF that allows the estimation of the age effect. First, it defines that intelligence of a child has two components, innate intelligence at the moment of birth and a malleable mental capacity which is function of age. Second, it defines that investment in cognition have different returns due to the mental capacity. That is, at different ages, the cognitive return is nonnegative to any investments. Third, based on the theoretical model discussed previously, there are two define periods that may incentive different responses by parents and schools actos. At the moment to start academic school, students with the same mental capacity start with different levels of human capital due to prior differentiate investments. At this moment, also, students with different mental capacity start with different accumulation of human capital due to mental capacity and parental responses. Moreover, from the supply side, government regulates the rules and requirements to start formal education. As government regulates the school entry age, any cutoff have implications on minimum age, average age and age dispersion which is translated into levels of mental capacity across children starting first grade. That is, these cutoffs have implications on how equal is the starting point to new entrants. Finally, taking these considerations into account, a causal model is developed to understand the components of the age effect in third grade; these parameters are the accumulated effect delayed one year of formal schooling in third grade.

Proposition 1 - Cognitive endowments - . A person's initial cognitive endowments are the sum of innate intelligence (I) plus mental capacity which is malleable and a function of age.

The optimal cognitive achievement schedule is based on the cognitive endowments, and how the developmental stages respond to the external inputs which are function of age. Wang and Aamodt (2010) argue that " Genes provide the blueprints for your child's individuality, but the plans are certain to be modified during construction depending on local conditions-not only parent's actions, but also your child's culture, neighborhood, teachers, and peers" (p. xxi). Assume that chronological age is reliable measure of the various stages of biological, physical, emotional and social development which allows to identify what an individual should learn at that any developmental stage; for example, education systems base their admissions in individuals' age.

$$CognitiveEndowment_i = G(Intelligence_i, Age_i) \tag{4.16}$$

where Age $\varepsilon\,[0,+\infty)$

Therefore, the cognitive achievement is a function of age from birth to the time optimal schooling is completed. According with Berninger and Richards (2002), "Thanks to the biological development during the first year of life, the child learns from what the genetic program says to acquire, from the stimuli from parents and from external experiences" (p.). That is, in the first year of life, the cognitive achievement is function of innate intelligence (I), household inputs-and external inputs (factors endogenous to the parents' optimization problem). While it is clear parents optimize resources as a function of their children's age, parents do not possess perfect information regarding the cognitive achievement on their child. Moreover, according with Todd and Wolpin (2003), "The effect of the capacity endowment while allowed to vary with age does not depend on current or past inputs" (F.23).

Proposition 2 - Innate ability constant overtime

Though the innate ability contribution to cognition is constant over time, parents adjust their optimal inputs to cognitive development to reflect the "observed" cognition of their child. In this model, innate ability influences represent a small proportion of cognition over time.

Proposition 3 - Cognitive returns to scale

A key assumption in this model is that people selects their optimal cognitive achievement schedules to maximize high returns through early investments (Berndt, 1990). In the educational production function, there are three define periods of mental capacity; the first period starts at the moment of birth to the age of three. The second period is around the age of 3 until around the age of 6. Finally, the third period begins at the age of 6 and ends when compulsory schooling ends. That is, there are different types of returns to cognition. So while resources can be invested at any time, mental capacity maturation induces different returns to differently timed investments.

Before the age of 3, cognitive achievement is represented as a function of previous cognitive achievement, current household inputs and current external inputs. That is, learning is the result of internal developmental trajectories and interactions with the world (though similar production functions aggregate this prior accumulation as innate ability).

Moreover, around this age, children have reached a development stage that allows for greater and greater learning. For example Bjorklund (2011) claim, " At the age of 3 or 4, children's brains are in the midst of hooking up their intuitive understanding of quantity with an explicit, later-developing sense of abstract numbers" (p. 208). Also, in some countries, at the age of 3, individuals are eligible to start kindergarten. Therefore, the cognitive achievement of a child at age $t = 3$ is an accumulation process which is a function of the achievement in previous years, current household inputs and potentially, extra-household experiences like kindergarten. Assuming that Kindergarten is intended to the stimulation in development skills, parents enrollment decision is primarily based on the cognitive return to kindergarten which in this model is assumed to be positive.
Whereas the empirical evidence in economics does not distinguish between school experiences before academic instruction (kindergarten) and formal academic instruction, developmental theory clearly distinguishes between these two periods. In particular, the decision to enter kindergarten is based upon different factors than the decision to enroll in the 1st grade of formal academic instruction. For instance, kindergarten entry-age may be related to early development skills while enroll 1st grade enrollment may be related to literacy development.

Proposition 4 - Cognitive Heterogeneity starting formal education

Cognitive achievement is heterogenous across individuals of the same age before academic instruction. The informal learning experiences which result from family resources and kindergarten engender individuals with different patterns of achievement long before staring formal education. Berninger and Richards (2002) mention that "considerable research on child development during the preschool years has shown that developmental trajectories in the following domains show variability across individuals of the same age and within the same individual: gross motor, fine motor, receptive language for understanding speech, expressive language for communicating, cognition and thinking, social-emotional, executive functions, and attention. The intra-individual developmental variation should not be surprising given the different brain systems are involved in each domain" (p. 299).

Prior to formal education, the main differences across children of the same chronological age are due to previous accumulation and contemporaneous parental and external resources as well as any kindergarten experiences. It is assumed here that children's mental capacity for abstract thinking is orthogonal to the development of children's social development. In other words, a child at age 6 can be capable of more abstract thinking necessary for formal school but still be slower with respect to social developmental stages or vice versa. In this respect, it is assumed that kindergarten is designed for an specific developmental stages as gross motor, expressive language for communicating, social emotional, executive functions or attention, while the academic education is designed for higher developmental stages like cognition and abstract thinking. Preschool can signalize that children have matured their first specific developmental stages and they are ready for more complex social context named school. Bedard and Dhuey (2006) state that " One should expect weak relative age effects in countries where formal curriculum based education begins later because initial age differences will be less important. " (p.4).

Proposition 5 - Parental decision rule

Parents will also decide to enroll children in academic instruction based on age eligibility. One way of representing this decision process for child i is the effect of one year of schooling at the age of t in comparison with a non-academic schooling at the age of t. However, the expected return of schooling depends on the school the child will attend. It is assumed, having the choice, parents will select a school which maximizes expected cognitive achievement.

Generally speaking, eligibility for enrollment to any kind of schooling is based upon the belief the child is ready, either by age or developmental maturity, to maximize cognitive achievement. Suppose when a child is eligible to enroll first grade (age based admission), parents choose child's optimal timing to enter to school based on the considerations that involve opportunity costs (including options), the cognitive achievement of the child, and the preferences of parents towards education given their resources. That is, parents make these decisions by taking into account the benefits and costs of starting formal education at age t. The parental decision is a function of the expected return of schooling (conditioned by school inputs) at age t. In addition, parents may see kindergarten as an exit certificate signifying the child is ready for formal schooling.

Proposition 6 - Cognitive Heterogeneity, School Eligibility and intra age variation

Eligibility to start formal education aggregates children who are all born within a 365-day period. This policy increases the variability of cognitive achievement levels among 1st graders as mental capacity will vary due to age ceteris paribus family resources and the developmental stages. Imagine two children—one born January 1 and one born December 31 in the same calendar year. Both would belong to the same chronological age group for purposes of enrollment eligibility, but are likely at different stages of biological, emotional, social or mental development. Nevertheless, parents typically do not know the cognitive achievement of child i at age t, and thus not know if their child is ready to start formal instruction in math and other skills. But still parents must still decide when to start the formal education of their child given the entry-age law imposed by authorities and the relative age of their child compared to peers.

Proposition 7 - Maturity cutoff

From the supply side, government regulates the rules and requirements to start formal education. However, it is still not clear, the direction of such regulation to make starting point equal and fair to all new entrants. In reality, however, education systems inevitably attempt to "optimize" this timing by using more or less arbitrary cut-offs. That is, "institutional knowledge" determines the minimum mental capacity necessary to benefit from schooling as well as the minimum level of social, motor and physical maturity to interact in the more demanding academic and social context of formal education. As government regulates the school entry age, any cutoff have implications on minimum age, average age and age dispersion which is translated into levels of mental capacity across children starting first grade. That is, these cutoffs have implications on how equal is the starting point to new entrants.

Proposition 8 - Educational Trajectories - Parental decision rule and Institutional rules

Educational trajectories are a function of mental capacity, but also depend upon parental decisions and resources as well as institutional factors. In addition, school authorities and teachers may react to parental decisions and this may impact the cognitive production of children through school inputs. The interaction of parental and institutional forces affects children's cognitive achievement trajectories.

A Causal Model In order to understand the causal effect of schooling and age, analyses extend to a model developed by Todd and Wolpin (2003). Taking into account these propositions and the relationships among age, schooling and test scores, the regression framework is based on differences between those equal in expectation that differ in school entry age. Imagine a child who was born the first day of the calendar year and starts an education accumulation process since the first moment of life. This model expresses the theoretical arguments behind cognitive achievement during early childhood and during school. In this first approach, it is assumed that unobservable factors do not impact the cognitive achievement. In terms of notation, age is equal to a full year.

Following the specification by Todd and Wolpin (2003), the model (including test scores as dependent variables and measurement of error) ($\varepsilon_{\mathbf{ija}}$) is given by:

$$\mathbf{T_{i,j,a}} = \mathbf{T_a}(\mathbf{F_{ij}}(\mathbf{a}), \mathbf{S_{ij}}(\mathbf{a}), \mu_{\mathbf{i0}}, \varepsilon_{\mathbf{ija}}) \tag{4.17}$$

$\mathbf{F_{ij}}(\mathbf{a})$ is a vector of parental inputs (current and past) at age **a** and $\mathbf{S_{ij}}(\mathbf{a})$ is a vector of school inputs (current and past) at age **a** (For more details, see Todd and Wolpin (2003) model). This model provides a framework to understand the role age plays in the children's cognition.

A child born the first day of the calendar year starts the accumulation process at the moment of life, $A = 0$, where innate ability accounts for initial cognitive achievement (Proposition 1 and 2). The equation is :

$$\mathbf{T_{i,0}} = \mu_{i0} + \varepsilon_{ija} \tag{4.18}$$

Moreover, cognitive achievement prior to formal education is the sum of innate abilities, the returns on family resources (β_{ia}) at different ages and the efficiency of those mental abilities(γ_{ia}) prior to academic instruction (Kindergarten can be included in this equation, as reflected in Propositions 3, 4, 6 and 7). Equation 4.19 shows the parameters of the EPF prior formal schooling:

$$\mathbf{T_{i,5}} = \mu_{i0} + \begin{bmatrix} \beta_{i1} \\ \beta_{i2} \\ \beta_{i3} \\ \beta_{i4} \\ \beta_{i5} \end{bmatrix} F(A)' + \begin{bmatrix} \gamma_{i1} \\ \gamma_{i2} \\ \gamma_{i3} \\ \gamma_{i4} \\ \gamma_{i5} \end{bmatrix} A' + \varepsilon_{ija} \tag{4.19}$$

In this production function, family resources have different returns β_{iA} which depend upon the age of the child. In addition, age has a direct effect on cognition functioning: $\gamma_{it} > \gamma_{it-1}$ where this return is increasing $\gamma_{it} > \gamma_{it-1}$. According with Todd and Wolpin (2003), "inputs effects differ both by age at which the input is applied and by the distance in time from the achievement measure" (p. F23).

Parental Decision Rule

Nevertheless, parents have two options for their children: to enroll at age 6 or 7 (Proposition 5). These options may affect children's cognitive learning schedules as well as their educational trajectories.

Option 1 - Parents decide the child will enroll at the age of 6. The cognitive production function after a year in school is:

$$\mathbf{T_{i,6}} = \mu_{i0} + \beta_{it}{}' F(A) + \beta_{i6S_1} F_{i6} + \tau_1 S_1(A_6) + \gamma_{it}{}' A + \varepsilon_{ija} \tag{4.20}$$

After a year in school, the production function accumulates the return for one year of schooling τ_1 and the returns of parental resources β_{i6S_1} conditional that the child is in school.

Under this condition, the contrafactual of going to school at the age of six will be the difference between the cognitive production of this child going to school and not going to school at the age of six:

$$\mathbf{T_{i,6,s_1}} - \mathbf{T_{i,6}} = \left[\beta_{iS_1,6} - \beta_{i,6}\right] F_{i6} + \tau_1 S_1(A_6) + \varepsilon_{ija} \tag{4.21}$$

Equation 4.21 shows the difference on cognition at the end of the child's age of 6 between to enter to school or not. This equation is the difference between the family inputs with a child in the school and not in the school at the age of six and the school return to that year with a mental capacity of a

6 -year-old child. This difference is composed of the different returns to family resources with the child in the school and out of school $\left[\beta_{iS_1,6} - \beta_{i,6}\right]$ and the return to a year of schooling (τ_1). This last component is the schooling effect.

Option 2 - If parents decide the children enters academic instruction at the age of 7, the cognitive production function after a year in school will be:

$$\mathbf{T_{i,7}} = \mu_{i0} + \beta_{it}{}'F(A) + \beta_{i7S_1}F_{i7} + \gamma_{it}{}'A + \tau_1 S_1(A_7) + \varepsilon_{ija} \tag{4.22}$$

Equation 4.22 specifies the production function of this child entering school at the age of 7. In this production function, only family resources at the age of 7 are affected by the child attending school. While previous inputs were not affected by this condition, entering an older age gives the child one more year of family resources unconditional to school as well as greater mental capacities reflected not only on developmental maturity but also in the returns to schooling.

How does cognitive production change relative to with these two options? The effect of earlier enrollment is a tradeoff between mental efficiency versus more schooling (all things equal). The decision to enter one year younger to academic instruction can be analyzed following this individual in these two educational trajectories. The differences in schooling can be analyzed as the intensity of the treatment maintaining mental capacity constant. For example, Equations 4.23 and 4.24 depict the cognitive function at age 8 for both options.

Starting younger—**option 1**—gives an additional return to one more year of schooling τ_{3A_8}, which represents a fixed school input with higher cognitive achievement than a previous grade $\tau_3 > \tau_2$. Under this option, parental resources are relative to enrollment at age 6 $\beta_{i6S_1}, \beta_{i7S_2}, \beta_{i8S_3}$.

$$\mathbf{T_{i,8,EA=6}} = \mu_{i0} + \begin{bmatrix} \beta_{i1} \\ \beta_{i2} \\ \beta_{i3} \\ \beta_{i4} \\ \beta_{i5} \end{bmatrix} F(A)' + \begin{bmatrix} \beta_{i6S_1} \\ \beta_{i7S_2} \\ \beta_{i8S_3} \end{bmatrix} F(A)' + \begin{bmatrix} \tau_{1A_6} \\ \tau_{2A_7} \\ \tau_{3A_8} \end{bmatrix} S(A)' + \begin{bmatrix} \gamma_{i1} \\ \gamma_{i2} \\ \gamma_{i3} \\ \gamma_{i4} \\ \gamma_{i5} \\ \gamma_{i6} \\ \gamma_{i7} \\ \gamma_{i8} \end{bmatrix} A' + \varepsilon_{isa} \tag{4.23}$$

Starting one year older—**option 2**—provides higher returns to schooling due to the higher mental efficiency and an extra year of parental resources without taking into account school inputs.

$$\mathbf{T_{i,8,EA=7}} = \mu_{i0} + \begin{bmatrix} \beta_{i1} \\ \beta_{i2} \\ \beta_{i3} \\ \beta_{i4} \\ \beta_{i5} \\ \beta_{i6} \end{bmatrix} F(A)' + \begin{bmatrix} \beta_{i7S_1} \\ \beta_{i8S_2} \end{bmatrix} F(A)' + \begin{bmatrix} \tau_{1A_7} \\ \tau_{2A_8} \end{bmatrix} S(A)' + \begin{bmatrix} \gamma_{i1} \\ \gamma_{i2} \\ \gamma_{i3} \\ \gamma_{i4} \\ \gamma_{i5} \\ \gamma_{i6} \\ \gamma_{i7} \\ \gamma_{i8} \end{bmatrix} A' + \varepsilon_{isa} \tag{4.24}$$

In this way, two different educational trajectories are possible (Proposition 8). However, the estimation of the impact of younger versus older enrollment depends upon estimating of the impact of schooling on cognitive production functions with different returns due to differences in mental capacity. That is, estimating the causal effect of school is not clear due to the efficiency of the brain early in formal schooling. Ceteris paribus the mental capacity, the causal effect of schooling on cognitive achievement is the differences between those who enter older and those who enter younger.

Due to the fundamental problem of causal inference, the empirical strategy cannot be estimated for child i. Thus, the empirical strategy is to consider the average treatment on the treated effect. The estimation of the treatment on the treated effect is summarized in Equation 4.25:

The Schooling Effect -

$$\mathbf{T_{i,8,s_3}} - \mathbf{T_{i,8,s_2}} = \begin{bmatrix} \beta_{iS_1,6} - \beta_{i,6} \\ \beta_{iS_2,7} - \beta_{iS_1,7} \\ \beta_{iS_3,8} - \beta_{iS_2,8} \end{bmatrix} F(A)' + \begin{bmatrix} \tau_{iS_1,6} - \tau_{iS_1,7} \\ \tau_{iS_2,7} - \tau_{iS_2,8} \end{bmatrix} S(A)' + \tau_1 S_3(A_8) + \varepsilon_{isa} \tag{4.25}$$

The differences in the education production function between these two options is equal to the differences in the returns to parental investment conditional on attending school at age 6 $\beta_{iS_1,6} - \beta_{i,6}$, plus the differences in returns to parental inputs at the same age but different grades $\beta_{iS_2,7} - \beta_{iS_1,7}, \beta_{iS_3,8} - \beta_{iS_2,8}$. In addition to the differences in returns to schooling within grade with different mental efficiencies $\tau_{iS_1,6} - \tau_{iS_1,7}, \tau_{iS_2,7} - \tau_{iS_2,8}$, plus the return to 3rd grade relative to age 8 ($\tau_1 S_3$). In this setting, The return to education assumes non-negative relation with age, thus in principle this difference $\tau_{iS_1,6} - \tau_{iS_1,7}, \tau_{iS_2,7} - \tau_{iS_2,8}$ should be negative.

The Age Effect in third grade -

Empirical evidence evaluates another counterfactual so as to understand the effect of age and schooling for a child with these two options. That is, it supposed that test score differences by age within a grade reflect an age-at-test effect. Another assumption is required to estimate the causal effect in this case. Within grade, the oldest and youngest below to two different chronological cohorts. Here, it is assumed these cohorts are equal in expectation. Equation 4.26 depicts the difference of test scores between those who are in the same grade but start one year apart. The difference comprises the return to family resources with the older child out of school $\beta_{i,6}$ plus the differences in returns to family resources conditional on each grade attended plus the returns to schooling to each grade and the effect of age at test. The differences in returns to education to each grade are expected to be positive due to age differences.

$$\mathbf{T}_{\mathbf{i},\mathbf{9},\mathbf{s_3}} - \mathbf{T}_{\mathbf{i},\mathbf{8},\mathbf{s_3}} = \beta_{i,6}F(A)_{i6} + \begin{bmatrix} \beta_{iS_1,7} - \beta_{iS_1,6} \\ \beta_{iS_2,8} - \beta_{iS_2,7} \\ \beta_{iS_3,9} - \beta_{iS_3,8} \end{bmatrix} F(A)' + \begin{bmatrix} \tau_{iS_1,7} - \tau_{iS_1,6} \\ \tau_{iS_2,8} - \tau_{iS_2,7} \\ \tau_{iS_3,9} - \tau_{iS_3,8} \end{bmatrix} S(A)' + \gamma_9(A_9) + \varepsilon_{isa} \tag{4.26}$$

According to Elder and Lubotsky (2009), the estimation of these effects should include not only the age at test but also the entry age and the time in school: "The test score differences by age within a grade reflect both the effect of kindergarten entrance age on scores and the effect of current age on test scores. It's not generally possible to separate these effects since entrance age, current age, and accumulated schooling are perfect collinear among track children" (p. 647). In fact, Black et al. (2008) argue that " Most of the literature has compared test scores of children who are in the same grade and so has in fact estimated the combined effects of school starting age and age (at the test) " (p. 3). According with equation 4.26, the comparison between the oldest and youngest (even in an experimental procedure) may overestimate the age-at-test effect (in the previous equation is γ_9) if there is no information on past and current decision rules by parents and schools. That is, this equation shows the accumulated effect of age on learning in third grade which includes the direct age-at-test effect, and indirect effects conditional on age since formal schooling started.

From this theoretical perspective, the practice of "red-shirting" mentioned earlier influences not only direct entry-age and age-at-test effects, but also influences family and school inputs during the extra year out of school. While this debate centers on how individuals can benefit most from school and personal experiences, the issues are enriched by incorporating all the effects of a policy not just the effect of mental capacity. Under equation 4.26 redefines this concept into a combined cluster of factors conditional on one year of delayed formal schooling. Yet discussion of "red-shirting" is more common in the United States since other countries have different practices of eligibility and admission. For example in Israel, Lavy et al. (2012) points out, " The Ministry protocol specifies that the kindergarten psychologist and teachers are in charge of identifying those children who are not ready for entry to 1st grade and who would rather spend an extra year in kindergarten" (p. 3).

This theoretical discussion also needs to be extended, however, to incorporate the effect of delaying school entrance on other school inputs which also impact learning. In particular, researchers have studied, without a theoretical framework, the effect of relative age as a result of delayed school entrance practices or as a result of changes in the cut-off age. The principal argument is that changes in school-entry age change the relative age in the classroom, which is defined as the differences in age between individuals who perform an activity in a group (Barnsley and Thompson, 1988). This occurs when a child's delayed enrollment increases the child's absolute age and modifies the relative age of the group (Black et al., 2008; McEwan and Shapiro, 2008). Lavy et al. (2012) argue that peer effects are important school inputs that affect student performance in school, and therefore changes in relative age may impact peer learning. Some authors claim that the effect of relative age on student performance may favor the oldest students (Deming and Dynarski, 2008). For example, Bedard and Dhuey (2006) argue that " Relative age differences at the start of formal schooling may therefore be long-lasting if relatively older students are better positioned to accumulate more skills in the early grades because their maturity advantage increases the likelihood that they are selected for more advanced curriculum groups or because they progress through a common curriculum at a faster rate". In this way, relative age may change individual opportunities for the youngest and oldest children (Barnsley and Thompson, 1988).

Pursuing the effects of relative age further, Elder and Lubotsky (2009) agree that " There are several reasons why the average age of a class may influence student outcomes. First, an older class may have fewer disruptions or allow a teacher to focus on more advanced material. Second, the achievement or behavior of older students may have a positive spillover effect on younger students. Alternatively, a child's own age may matter only through its effect on the child's location in the classroom age distribution" (p. 651).

Chapter 5

The Educational Disadvantages of the Indigenous Population of México and its consequences

5.1 Introduction

> Es mas facil uniformar y emparejar, que integrar armonicamente. El ideal es un México integro
>
> Sáenz (1939)

In México, indigenous peoples are—and have been—the most disadvantaged population since the times of the Spanish conquest. (Ramirez, 2006). According to Sáenz (1939), being indigenous in México is not only a racial or biological classification; being indigenous is a social condition. The persistent poverty that the indigenous population faces is one of the most critical challenges confronting economic development in México. Despite significant improvements in the educational coverage and average educational attainment over the past several decades, considerable differences remain between indigenous and non-indigenous populations. First, illiteracy and drop-out rates continue to be substantially higher among indigenous families. Second, among indigenous families, children are less prepared to start formal education. Third, educational opportunities (i.e., access, learning environments, outcomes, and transitions to subsequent educational levels), are fewer. Finally, even when educationally successful, indigenous peoples do not receive the same monetary returns to their investments in education as do non-indigenous peoples.

This chapter analyzes educational inequities between indigenous and on-indigenous populations and their socioeconomic consequences. Section 5.2 describes the data. Education inequities are discussed at length in Section 5.3. Additionally, Section 5.4 analyzes poverty and income disparities in México while Section **??** reviews how these economic conditions relate to educational contexts. Section 5.5 details the monetary returns accrued through investments in education. Finally, Section 5.6 concludes with policy suggestions for improving the educational condition of the indigenous population of México.

5.2 Data and Demographics

For most of the rest of the 20th century the only criterion used by the government to identify indigenous people was language. The single focus on the linguistic capability of the population as an indicator of ethnicity, however, has a number of limitations. It was not until 1997 that a National Employment Survey used self-perception, in addition to language, as a means to identify indigenous people. And it was not until 2000 that self-perception was reintroduced as an indicator of ethnicity to the National Population Census. Since 2008, the National Income and Consumption Survey identifies Indigenous population by the linguistic capability of the population and self-identification.

Ethnic identity is a complex phenomenon that cannot be reduced to language alone. In the case of Mexico, however, language spoken is perhaps the most reliable and objective proxy for ethnicity. In addition, it is the only indicator of ethnicity that allows us to analyze historic trends. In the present analysis, all the speakers of an indigenous language 5 year of age or older were counted as indigenous. In addition, all individuals that are part of a household where the household head or his/her spouse speak an indigenous language were also counted as indigenous. The self-identification criterion was not used because it does not allow for inter-temporal comparisons. The indigenous population of Mexico is predominantly rural (communities with fewer than 15,000 inhabitants). In terms of geographical distribution, the indigenous population is primarily concentrated in the southern region of the country.

The current analysis relies on data from the National Income and Consumption Survey (Encuesta Nacional Ingresos y Gastos de los Hogares, ENIGH) which, for the first time in 2008 and then 2010 identified indigenous populations by two criteria: the linguistic capability of the population and self-identification. The ENIGH survey is carried out biannually and collects information on household income (including property rentals and public transfers), education and employment at the national level in both urban and rural areas. Following the poverty measure methodology developed by CONEVAL, the survey provides detailed household expenditures for education, which improves over the data available in previous studies, which includes instead general education expenditures on education.

An indigenous variable was constructed from the survey by using a technique which combines the indigenous variable in the survey and household membership. This contrasts with previous studies which did not have access to data with a variable that could be used to identify an indigenous person and, instead, relied on geographical considerations, identifying people who reside in "indigenous municipalities"—where at least 30% of the population speak an indigenous language. Previous ENIGHs (1989-2006) indeed lacked a variable identifying indigenous people, but through matching methods researchers were able to impute the likelihood that an individual or family was indigenous by their geographical location. This matching method has a natural bias since it focuses on the characteristics of indigenous individuals who live in municipalities with high density of indigenous populations. The data set used in this chapter, however, includes individuals who live in all types of municipalities, including municipalities which do not have a huge percentage of indigenous people. The analysis below is performed using the indigenous criterion asked in ENIGH 2008 and 2010.

In addition to more accurately representing indigenous populations, the ENIGH 2010 data tracked multiple sources of income. Total current income was defined as the sum of two components: monetary and non-monetary. Monetary income includes wages, income from self-employed or entrepreneurial activities, income from cooperative societies, businesses, and firms, rent of non-domicile properties or assets, and transfers. Non-monetary income includes production for own, in-kind payments, and the estimated value of renting a domicile home. In order to properly express the value of income and expenditures (for non-monetary income), deflation rates for income and expenditures were independently specified. Moreover, for the purpose of this study, indigenous communities were analyzed because they are more similar in both characteristics (infrastructure, schools, production, etc.) and in outcomes than non-indigenous communities. Other data is drawn from the indigenous criterion surveyed in ENIGH 2008 and 2010. The main sources of educational data were from the Mexican Ministry of Education, which collects a range of information, from assessment data to household characteristics along with national, state and type of school modality representativeness.

In addition to the data obtained from ENIGH 2008 and 2010, this chapter uses educational data from the Mexican Ministry of Education, which collects a range of information, from assessment data to household characteristics along with national, state and type of school modality. In order to track their data, the Ministry of Education issues each school a number which, in turn, allows researchers to identify schools across different data sets. In addition, each student is associated with a single unique code. This dual-code system allows data from many diverse sets to be aggregated and analyzed.

The present study also uses information from fourteen rounds of the School Census Data (SCD). The SCD specifies the geographic location of schools, the distributions of age in each grade, the percentage of 1st graders who attended kindergarten, and general information regarding teachers and school facilities.

As for data on student characteristics, including student achievement, this study relies on the data provided by ENLACE (Evaluación Nacional de Logro Académico en Centros Escolares). The ENLACE test is a census-based assessment which examines student performance in mathematics and Spanish. In connection to ENLACE, selected schools were given two questionnaires—one for principals and one for students—to complete. All in all, the ENLACE tests and the ENLACE surveys provide a comprehensive data base covering students from the 3rd to the 9th grade, including student and parental characteristics.

5.2.1 Indigenous population

In México, indigenous populations have two main geographic characteristics: most indigenous households live in concentrated areas and they tend to reside as well in rural communities. Of the entire indigenous population, only 28% live in urban areas. As Ramirez (2006) argues, "The high concentration of indigenous populations in rural areas is even more marked for the monolingual indigenous population" (p. 152).

The majority of indigenous people in México live in rural areas in the south of the country. By way of comparison, while more than 50% of the indigenous population lived in rural communities with fewer than 2,500 inhabitants in 2010 only 25% of the overall Mexican population lived in such small communities. This percentage increases to a full 70% when the community numbers 15,000—almost double the comparable national average of only 39%. These indigenous areas are principally located in Chiapas (32%), Yucatan (51%), Oaxaca (43%), Quintana Roo (35%), Campeche (24%) and Tabasco (5%) (see Table 5.22 in Annex).

The composition and characteristics of the indigenous household differs from the rest of the population. The indigenous household has more family members and, on average, more children (see annex 5.27). In fact, 19 percent of non-indigenous households were managed by a female head of the household, while only 14 percent in indigenous communities (above 70 percent indigenous inhabitants).

In addition, Table 5.1 details how age distributions differ between indigenous and non-indigenous households. For instance, in 2000, 60% of the Mexican population was below the age of 30 (with no difference between indigenous and non-indigenous households). However, by 2010, only 54% of the non-indigenous population was still below age 30; the figure for indigenous communities remained at 60%. By the same token, the plurality of the indigenous population is aged between 4 and 15 years while 15 to 29 year olds constitute the plurality of the non-indigenous population. In this way, indigenous households have more members and they are younger on average.

Table 5.1: Age Distribution of Population by Municipality

	2000				2010			
	Non-Indigenous	Indigenous		All	Non-Indigenous	Indigenous		All
		1	2			1	2	
Younger than 5	10	10.7	10.6	10.1	8.76	8.9	11.03	8.89
5 to 14	23	26.2	27.6	23.4	19.77	21.08	24.51	20.09
15 to 29	27.2	24.7	21.4	26.9	25.88	27.13	24.9	25.88
30 to 44	19.6	20.4	17.3	19.6	20.77	20.86	17.08	20.57
45 to 59	12.2	9.6	12.4	12.1	14.69	12.86	12.41	14.48
Older than 59	7.9	8.4	10.7	8	10.13	9.18	10.07	10.09

Source:Author's calculation using ENIGH 2000 and 2010.
Non-Indigenous refers to 0% to 30% of indigenous in the municipality
Indigenous 1 refers to 30% to 70% of indigenous in the municipality
Indigenous 2 refers to 70% to 100% of indigenous in the municipality

5.3 Education inequities

5.3.1 Human capital endowments

Indigenous populations have faced, and continue to face, significant socioeconomic disadvantages (Lunde et al., 2007). Indigenous children are born into poorer environments, live poorer lives and have poorer children.

Language

The issue of language is an essential one to consider in examining the indigenous population. The data show that the proportion of monolingual indigenous people in México has decreased at an even faster rate than the proportion of indigenous language speakers in the population as a whole. As Table 5.2 shows, in 1930, over half of the indigenous language speakers did not speak Spanish. In 2010, by contrast, only 15% of indigenous language speakers could not speak Spanish. This trend towards bilingualism reflects the integration efforts of post-revolutionary governments, among which bilingual education has played an important role.

Table 5.2: Proportion of Monolingual and Bilingual indigenous people, 1930-2000

Year	Indigenous Population*	Monolingual %	Bilingual %
1930	2,250,943	52.7	47.3
1940	2,490,909	49.7	50.3
1950	2,447,609	32.5	67.5
1960	3,030,254	36.5	63.5
1970	3,111,415	27.6	72.4
1980	5,181,038	22.7	71.4
1990	5,282,347	15.8	80.2
1995	5,483,555	14.7	84.8
2000	6,044,547	16.9	81
2010	6,695,228	14.6	

Source:INEGI 2012.

The monolingual population is increasing with age; the oldest generation constitutes the highest proportion of the monolingual populations (for more information see table in the annex).

Literacy

One of the most important skills in any society is the ability to speak—and read—the official language. Unfortunately, these critical skills are negatively correlated with ethnicity, age and gender: indigenous peoples are less likely to speak and read in Spanish than non-indigenous; while a significant proportion of older people do not read and write, and women have higher illiteracy rates. These factors can be combined to generate sharp inequities: the majority of older indigenous people are illiterate; and, on average, indigenous males are much more literate than females.

In 2000, the illiteracy rate among the elderly living in non-indigenous municipalities (with less than 30% of indigenous inhabitants) was 30.2%. The comparable rate within indigenous municipalities was 69.3%. By 2010, this illiteracy among the elderly in indigenous communities doubled. (for within gender data, see Tables 5.23 and 5.24 in Annex).

Table 5.3: Literacy by Municipality

	2000				2010			
	Non-Indigenous	Indigenous		All	Non-Indigenous	Indigenous		All
		1	2			1	2	
5 to 14	78.9	76.3	70	78.4	83.43	81.3	79.09	83.04
15 to 29	95.9	94	80.9	95.4	98.35	96.43	93.48	98
30 to 44	92.6	86	63.5	91.3	96.14	90.71	79.36	95.13
45 to 59	86.4	71.4	56.5	84.7	92.93	82.96	65.27	91.23
Older than 59	69.8	53.4	30.7	67.1	80.13	61.25	41.85	77.27

Source:Author's calculation using ENIGH 2000 and 2010.
Non-Indigenous refers to 0% to 30% of indigenous in the municipality
Indigenous 1 refers to 30% to 70% of indigenous in the municipality
Indigenous 2 refers to 70% to 100% of indigenous in the municipality

Schooling

In the decade 2000-2010, Mexican schooling has expanded. In 2000, the average years of schooling was 8.2 years; in 2010 it reached 9.2 years. Patrinos and Metzger (2004) argue that there has been substantial progress in raising the enrollment rates of both indigenous and non-indigenous populations, especially in basic education. In fact, municipalities with the highest concentrations of indigenous populations increased their schooling levels by 2.9 years. By contrast, non-indigenous communities increased their schooling only one year. This narrowing of the schooling gap by 1.8 years, significant as it is, did not eliminate the 1.9 years of schooling difference that still exists between these groups.

Table 5.4: Average Years of Schooling by type of Municipality

	2000			2010		
	Non-Indigenous	Indigenous	All	Non-Indigenous	Indigenous	All
	0% to 30%	30% to 100%		0% to 30%	30% to 100%	
Ave. Years Schooling	8.31	4.55	8.18	9.33	7.4	9.15

Source:Author's calculation using ENIGH 2000 and 2010.

Furthermore, between 2000 and 2010, the number of individuals aged 15 and above attending school in México increased by 2%. In non-indigenous communities, this figure increased by only 1.8%, but in communities with the highest concentration of indigenous people, school enrollment for this age group jumped by 5.1%. Again, while encouraging, this narrowing still leaves a 3% gap. At this rate, ten more years would be needed to redress the imbalance.

Table 5.5: Age Distribution of Population by Municipality

	2000				2010			
	Non-Indigenous	Indigenous		All	Non-Indigenous	Indigenous		All
Population aged 15 and over		1	2			1	2	
Still in school (%)	10.8	8.3	4.6	10.4	12.6	12.3	9.7	12.4
If not still in school, highest educational achievement								
No Education	25	36.7	59.4	26.8	17.7	27.1	39.9	19.2
Incomplete Primary	6.2	7.6	9.7	6.4	4.5	5.5	7.6	4.7
Complete Primary	25.6	20.7	19.8	25.1	22.1	18.7	21.1	21.9
Complete Lower Secondary	25.4	23.1	6.9	24.6	27.9	25.2	19.7	27.4
Complete Upper Secondary	7.2	5.7	1.5	6.9	16.1	15.4	7.9	15.6
Complete University	10.2	6	2.7	9.7	10.6	7.4	3.6	10.1
Graduated school	0.6	0.3	0	0.5	1.2	0.7	0.2	1.1

Source:Author's calculation using ENIGH 2000 and 2010.
Non-Indigenous refers to 0% to 30% of indigenous in the municipality
Indigenous 1 refers to 30% to 70% of indigenous in the municipality
Indigenous 2 refers to 70% to 100% of indigenous in the municipality

Table 5.5 illustrates human capital endowments for municipalities with different concentrations of indigenous speakers. Municipalities with the lowest concentration of indigenous people have higher human capital endowments. In 2000, 18% of the wealthiest population completed high school or higher education, in contrast to a mere 4.2% among municipalities with a population of 70% or more of indigenous people. Within the latter communities, about 60% of the population lacks schooling, and another 10% have less than a grade 6 education. By 2010, however, human capital assets increased at all levels of education across Mexican society: 2% more completed primary school, 13% more completed 9th grade, 6.5% more completed 12th grade, and 0.9% more completed university. Yet, educational disparities persist between indigenous and non-indigenous communities. The former have 22.2% more inhabitants without any education and lower levels of education.

Gender also plays a role. Among males, educational differences between indigenous and non-indigenous have decreased over time (see Tables 5.25 and 5.26 in Annex). But for females, these differences have actually increased. Indigenous females have the lowest levels of academic instruction and are consistently among the most disadvantaged groups in the country. However, in absolute levels, the greatest advancements between 2000 to 2010 were made among this group.

Using the ENIGH 2010 and SDC definitions of indigenous, Figure 5.1 displays educational diversity by age, gender and ethnicity: Overall, males and females are about equal, older generations are less educated than younger generations, and those in their twenties have the highest levels of education. Yet, even among the youngest generations, the gap between indigenous and non-indigenous, though closing, remains significant.

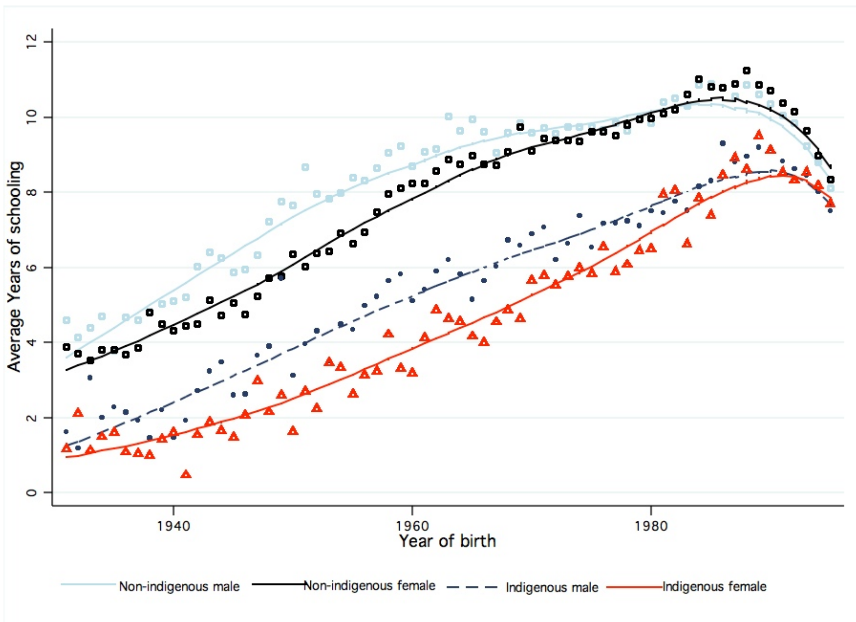

Figure 5.1: Average Years of Schooling by Year of Birth. Source:Author's calculation using ENIGH

Using ENIGH 2010 data, Table 5.6 shows the distribution of years of schooling among males and females aged 15 and older for both ethnic groups. For age 15 and older, schooling is negatively correlated with age, being female or indigenous. Combining these three factors of inequality, the most disadvantaged individuals are the oldest indigenous females, aged 60 or older, with only 1.2 years of schooling—a gap of 9.1 years of formal education relative to non-indigenous women aged 15 to 30. Differences by ethnicity decrease for the youngest cohorts. The difference between female indigenous and non-indigenous populations aged 15 to 30 is only 1.9 years of schooling.

Table 5.6: Average schooling by Ethnicity and Age

	Non-Indigenous		Indigenous		All
	Male	Female	Male	Female	
60 and older	5.5	4.6	2.3	1.2	4.7
45 to < 60	8.8	7.7	5.1	3.5	7.9
30 to < 45	9.7	9.4	6.9	5.8	9.2
15 to < 30	9.9	10.3	8.4	8.4	10
4 to < 15	3.5	3.7	3.3	3.4	3.6

Source:Author's calculation using ENIGH 2000 and 2010.
Indigenous defined as living in households where one or more members speak an indigenous language or who identified themselves as indigenous.

Finally, measured by the Gini coefficient, educational inequality increases with ethnicity (see Table 5.7). That is, the dispersion with respect to the mean years of schooling for indigenous populations is greater than for non-indigenous. In addition, the education endowment has greater dispersion for people aged 45 and older. Educational disparities have decreased among the younger cohorts.

Table 5.7: Educational Inequality, Gini Index

	Gini Index		
Age	Indigenous	Non-Indigenous	All
Younger than 5	0.22	0.03	0.05
5 to 14	0.36	0.36	0.36
15 to 29	0.19	0.17	0.18
30 to 44	0.29	0.23	0.24
45 to 59	0.38	0.3	0.31
Older than 59	0.4	0.37	0.38
All	0.34	0.31	0.32

Source:Author's calculation using ENIGH 2000 and 2010.
Indigenous defined as living in households where one or more members speak an indigenous language or who identified themselves as indigenous.

In conclusion, there is ample evidence for great disparities in human capital across ethnicity, gender, age and location in México. Indigenous people, however, are the most disadvantaged group in México.

5.4 Economic initial conditions of Indigenous people: The poorest population in México

Most indigenous people live in small rural communities, often located in remote areas with limited access to economic markets (Lunde et al., 2007). For these communities, the main source of income is related to agricultural work.

For consistency and comparison, this study examines the incidence of poverty among municipalities of different indigenous concentrations using two national poverty criteria developed by (CONEVAL, 2014), one for extreme poverty and one for moderate poverty. The extreme poverty line is set at the per capita household income necessary to acquire basic consumption goods. The moderate poverty line is set at an income level necessary to cover basic education, health, housing, clothing and public transportation as well as the basic food consumption.

Table 5.8: Evolution of Poverty, 1992-2002. Head Count Index (P0)

Population	1992	1994	1996	1998	2000	2002	2004	2006	2008	2010
Extreme Poor										
Indigenous	70.8	69.2	83.7	65.1	85.4	68.5	68.1	51.5	55.1	51.9
Non-indigenous	18.7	17.9	33.3	29.3	20.8	14.9	14	10.5	16	16.9
Rural	35.5	36.6	52.2	51.9	42.1	34.5	27.6	24.5	31.8	29.3
Urban	13.4	9.7	26.2	21.1	12.5	11.4	11	7.5	10.6	12.6
Total	22.4	21	36.9	33.7	24.1	20.3	17.3	13.7	18.2	18.8
Poor										
Indigenous	90	89.6	96.5	83.1	95.3	89.7	88.6	79.4	80.6	78.9
Non-Indigenous	49.1	52.8	67.2	60.3	50.6	46.7	44.4	39.3	45.3	49.6
Rural	64.8	71.9	80.6	74.7	69	67.3	56.9	54.7	60.8	60.8
Urban	43.8	43.2	61.4	55.4	43.5	42	41	35.6	39.7	45.5
Total	52.4	55.3	69.3	63.3	53.5	51.7	47	42.5	47.3	51.3

Patrinos and García-Moreno (2012)
Indigenous: more than 70% indigenous
Non-Indigenous: less than 10% indigenous

Table 5.8 presents Mexican poverty trends between 1992 and 2010. During this period, the extreme poverty rate declined by 3.6% while moderate poverty declined by 1.1%. In rural areas, extreme poverty decreased by 6.2%. By contrast, extreme poverty in urban areas declined only 0.8% and moderate poverty actually increased by1.7%. As for indigenous populations, extreme poverty among indigenous people decreased by 19% and moderate poverty by about 11% during this 18-year period. This reduction has not been enough, however, to bring the economic condition of this population to match that of the general population. All in all, these numbers confirm the findings of (Ramirez, 2006) who combined ENIGH and SCD data from 2002 to estimate poverty at the municipal level. The author found that the extreme poverty rate in indigenous municipalities was 68.5% and the moderate poverty rate is 89.7%.

Note, however, that according to Patrinos et al. (2012), “It is possible that the peak in indigenous poverty observed in 2000 is partly related to a significantly lower representation of indigenous municipalities in the sample of the 2000 ENIGH. While 17.2% of the municipalities sampled in the 2002 ENIGH had indigenous concentrations above 40% and 9.8% had indigenous concentrations above 70%, only 6.4% of the municipalities sampled in 2000 had indigenous concentrations above 40% and only 3.6% had indigenous concentrations above 70%” (p. 8).

Table 5.9 shows that 2008 and 2010 poverty rates, compared on the basis of ethnicity and monolingualism. Consistently, 94% of the monolingual population lives in poverty, while only 80% of the bilingual population does. Language, like location and ethnicity has also become an indicator of poverty.

Table 5.9: Poverty Distribution by ethnicity (%)

	2008				2010			
	Indigenous			Non-Indigenous	Indigenous			Non-Indigenous
	Monolingual	Bilingual	All		Monolingual	Bilingual	All	
Not Poor	6%	20%	19%	49%	6%	19%	18%	45%
Poor	94%	80%	81%	51%	94%	81%	82%	55%
Extreme Poor	80%	53%	56%	19%	82%	53%	55%	20%
Overall Population	8%	92%	8%	92%	13%	87%	7%	93%

Source:Author’s calculation using ENIGH 2008 and 2010.
Indigenous defined as living in households where one or more members speak an indigenous language or who identified themselves as indigenous.

In general, education is an indicator of poverty. Table 5.10 depicts levels of education by economic status and ethnic group. Indigenous populations which lack academic instruction have a poverty rate of 83% while comparable non-skilled, non-indigenous populations are poor at a rate of 63%. Of course, at higher levels of education, the percentage of people living in poverty declines for both ethnic groups.

Table 5.10: Poverty Incidence by Education Level

	Indigenous		Non-Indigenous	
	Poor	Extreme Poor	Poor	Extreme Poor
No Education	0.83	0.45	0.63	0.19
Incomplete Primary	0.78	0.43	0.61	0.17
Complete Primary	0.75	0.32	0.49	0.09
Complete Lower Secondary	0.66	0.19	0.4	0.04
Complete Upper Secondary	0.49	0.11	0.25	0.02
Complete University	0.19	0.02	0.09	0
Graduate school	0.06	0	0.02	0

Source: Authors calculations using: ENIGH-MCS 2010.
Interpret as, "For a given education level,
what is the percent indigenous or non-indigenous
people who will be poor?" Headcount

In order to determine the impact of increased education in reducing poverty, holding other things constant, a logistic regression using human capital, household assets and demographics as factors was carried out. The impact of increased schooling in reducing poverty is specified by introducing dummy variables for various levels of schooling into the equation. These levels are: incomplete and complete primary education, complete lower secondary education (9th grade), complete upper secondary (12th grade), complete university, and graduate education. The objective was to determine the importance of these levels of education as determinants of poverty. Indigenous populations are identified also by a dummy variable, so that the impact of being in this population on poverty, holding other things constant, can be examined.

Tables 5.28 and 5.29 show how age, level of education, the number of working-age residents in the household, the age of the household head, and the prevalence of non-agricultural work decrease the probability of being poor—both in the 18-year-old and older sample as well as in the household head sample.

The analysis shows that the variables with the greatest negative marginal impact on poverty for both samples are the highest levels of education: complete upper secondary, complete university and graduate school. These levels of education have a very significant impact in reducing the probability of being poor. The results indicate that attending primary school decreases the probability of being moderately poor by 4% relative to not attending school at all (holding other factors constant at their mean levels). Similarly, completing primary education decreases the probability of being moderately poor by 3% relative to not completing primary school. Similar trends govern other levels of education: completing 9th grade decreases the probability of being moderately poor by 3% relative to only completing 6th grade; completing upper middle education decreases the probability of being moderately poor by 4% relative to only completing lower secondary education. Post-secondary higher education decreases the probability of being moderately poor by yet another 3% relative to only finishing high school.

Living in a rural area and working in the agriculture sector are also associated with poverty. Salaried agricultural workers are 20% more likely to be moderately poor relative to salaried workers in other sectors of the economy (holding other things constant). Even agricultural owners have elevated rates of poverty. They are 13% more likely to be moderately poor relative to other business owners. The worst case, however, are non-salaried agriculture workers: They are a full 25% behind their non-agricultural peers.

The presence of children in the household also increases the probability of being poor. From an economic perspective, every additional young person below age 16 years the probability of being poor by 7%. This dynamic is particularly significant given the average Mexican household has 3 children under age 15—and the average indigenous household has 3.7 children below the age of 15. Finally, the possession of physical assets has always been a form of social protection, particularly for the poor. The indigenous population between 2000 and 2010 has registered significant progress in these areas, even when great differences continue to exist in access to services and in the physical conditions of homes.

According to the results in Table 5.29 living in an indigenous household increases the probability of being moderately poor by 11%. Note that this effect holds constant other factors, including schooling, and therefore either represents the direct impact of discrimination and prejudice on indigenous populations or the influence of factors omitted in the analysis. Nonetheless, what is important to recognize is that, following our earlier results in this Section, increased education can serve as a major force in reducing this poverty gap facing indigenous groups. The following sections examine in greater detail the issue of schooling and the labor market returns to education.

5.4.1 Educational opportunities

As commented in previous sections, in the last decade, indigenous people have increased their formal schooling, but significant educational discrepancies remain between indigenous and the non-indigenous communities. Moreover, indigenous students face substantial challenges in terms of the quality of their schooling (INEE, 2004). This section describes the educational opportunities available to indigenous communities in terms of access, learning environments, outcomes, and advances to higher levels of education. The data reveals that their educational "ladder of success" is steeper and longer as well more fractured and splintered.

Access

In México, considerable progress has been made in terms of increasing access to basic education. In the introduction, some of the educational indicators for México were presented. Some additional indicators are presented here, with a special focus on indigenous populations. In 2010, 96% of the population aged 6 to 12 attended school while just 20 years earlier, the figure was 86%. Similarly, the number of 13- to 15-year-olds who attended school increased 17% while enrollment among older students aged 16 to 19 increased by 14% and 6% for those aged 20 to 24.

Table 5.11: Population who attend school by age cohort

	1990	2000	2005	2010
6 to 12 years old	89	94	96	96
13 to 15 years old	69	77	83	86
16 to 19 years old	37	41	48	51
20 to 24 years old	16	18	21	22

Source: INEGI

In México, each educational level represents a challenge in terms of terminal efficiency. Table 5.12 depicts the drop-out rates by level of education and school year. In the last ten years, drop-out rates for the first six grades have decreased by 1.1%. Moreover, in grades 7 to 9, drop-out rates fell by 2.7% and high school drop-out rates decreased by 1% though still remaining above 15%. Even technical education which traditionally has the highest drop-out rate, experienced a decrease of 1.6% during the period 2000 to 2010.

Table 5.12: Drop out rate by education level and school term

School term	Primary	Secondary	Technician	High School
2000/2001	1.9	8.3	24.8	16.5
2001/2002	1.6	7.3	25.4	15.8
2002/2003	1.7	7.4	25.3	16.4
2003/2004	1.8	7.4	24.7	16.8
2004/2005	1.4	7.4	26	16.1
2005/2006	1.3	7.7	23.9	15.7
2006/2007	1.5	7.4	24.6	15.5
2007/2008	1.1	7.1	24.5	15.5
2008/2009	1.1	6.8	23.2	15
2009/2010	0.9	6.2	21.2	15.6
2010/2011	0.8	5.6	20.9	13.8

Source: INEGI

While drop-out rates track those students who terminate their education at a certain level, transition rates track students as they graduate from one level and move to the next. Between 2000 and 2010, the number of students who finished the 6th grade but did not enroll in the 7th grade decreased from 8.2% to 3.5%. In 2000, 81% of 9th year graduates enrolled in the 10th grade while in 2010, this figure increased to 87%. These data demonstrate how progress has been achieved in the transition from primary to lower secondary education, but indicate vulnerabilities in the transition from lower secondary to upper secondary.

Table 5.13: Transition rates -Percent of students who finish the previous level and enter to the next grade

School Term	Secondary	High School
2000/2001	91.8	81
2001/2002	93.4	84.6
2002/2003	94.1	84
2003/2004	94.7	85.4
2004/2005	95	85.1
2005/2006	94.9	84.9
2006/2007	95.4	85.6
2007/2008	95.2	85.5
2008/2009	95.5	86.9
2009/2010	95.7	86.9
2010/2011	96.5	87

Source: INEGI

Table 5.14 presents the results of a multivariate analysis of the determinants of school participation for children/youth aged 7 to 14. The exercise carries out an econometric analysis where the dependent variable is equal to one if the youth was enrolled in school and zero otherwise (a linear probability model). The explanatory variables included: (1) socioeconomic background of the youth, proxied by family income (MX pesos), parental education (mother's schooling), number of rooms in the housing unit where the child/youth resides, presence of running water and of a kitchen in the housing unit, (2) characteristics of the child/youth, including age, gender, number of siblings and residence in a location of high indigenous density.

The results of the analysis for 2000, indicate that the probability of being enrolled in school increases with parental education, household assets (number of rooms, water and kitchen), family income—and simply being male. On the other hand, the probability of school participation decreased with age, and with the number of siblings. By 2010, however, some of these factors were inverted. For example, the probability of enrollment increased with age, number of siblings and being female. These changes may reflect shifts in the costs and benefits of education for different groups as well as cultural changes. The increasing probability of employment among girls in, for instance, is a tendency observed in many other countries, and the results presented here reflect this worldwide shift as applied to México.

In terms of the indigenous population, the results for 2000 show that if the child/youth resided in an area of high concentration of indigenous people, it had higher enrollment rates, holding other things equal. In 2010, the coefficient of location in a concentrated indigenous location is negative, but very small in magnitude. These results suggest that, after holding family income and other socioeconomic and student characteristics constant, being located in a concentrated indigenous location has no negative impact on enrollment. The implication here is that, in terms of school enrollment, the shortfall in the enrollment of indigenous children in school may be closely linked to the lower socioeconomic status of these populations. This assumes –as is assumed here and most of the literature does—that indigenous populations are more likely to reside in areas where indigenous populations are concentrated.

Given the result obtained earlier, where indigenous status appears to be positively correlated with increased poverty, even after holding constant other variables, the implication here may be that prejudice and discrimination may not be as strong in schooling as it appears to be in income and the labor market. But such an implication would require much more detailed analysis than the exploratory work in this chapter.

Table 5.14: Determinants of Schooling Participation, Entire Youth Subsample

	2000				2010			
	Coef.	S.E.	Mean	MFX	Coef.	S.E.	Mean	MFX
Age	-0.15	0.000 ***	10.46	-0.011	0.2	0.000 ***	10.5	0.009
Male	0.1	0.001 ***	0.52	0.007	-0.03	0.001 ***	0.5	-0.001
Indigenous	0.01	0.000 ***	10.57	0.001	-0.002	0.000 ***	12.5	0.000
Mother's Schooling	0.1	0.000 ***	5.77	0.007	-0.09	0.000 ***	7	-0.004
No. Siblings	-0.07	0.000 ***	3.33	-0.005	0.1	0.000 ***	2.9	0.004
Rooms	0.12	0.001 ***	2	0.009	-0.08	0 ***	3.8	-0.004
Running water	0.24	0.001 ***	0.86	0.021	-0.1	0.002 ***	0.9	-0.005
Kitchen	0.04	0.002 ***	0.88	0.003	0.05	0.002 ***	0.9	0.002
Family Income	0	0.000 ***	1980	0.000	0.000	0.000 ***	2029	0.000
Constant	2.58	0.003 ***			-3.46	0.004 ***		
R-square	0.1587				0.1848			

Source: Authors' calculations based on ENIGH 2000 and 2010.
Ages 7 to 14.
*** 99% **95% * 90%
Indigenous Municipality is a continuous variable from 0 to 1

Learning environment

Before 2004, basic education covered only the 1st grade to the 9th grade. After the Mexican education law was reformed in November 2002, kindergarten was introduced as a compulsory element of basic education.

Table 5.15 shows the population of 1st graders who attended at least one year of kindergarten. In 1998, only 21% of 1st graders attending a community school went to kindergarten. By 2008, this figure had increased by 10 percentage points. Community schools are designed for rural, isolated communities with fewer than 100 inhabitants, and most of these communities have a very high proportion of indigenous people. Indeed, most indigenous schoolchildren attend either compensatory or indigenous schools. So, the increased proportion of community school first grade entrants with kindergarten is likely to apply to indigenous populations as well. But although it shows progress, note that the overall percentage is very small: less than one third of children in community schools entered first grade having being in a kindergarten, compared with 88% in the general public school population. The remaining gap is huge.

Additional information on the participation of indigenous children in kindergarten is given by the data for schools that are catalogued explicitly as indigenous schools. In 1998, 56% of indigenous

1st graders had attended a kindergarten. But by 2010, access to kindergarten for this population increased by 16 percentage points. So, these data again show progress in the enrollment of indigenous children in Kindergarten. At the same time, significant disparities remain between indigenous schools and the general public school population. The 72% figure for the percentage of new entrants into indigenous schools who have had Kindergarten in 2008, is much lower than the 88% for general schools.

These disparities create different starting points which in turn lead to different learning outcomes later in the children's school life.

Table 5.15: Percent of first enterers to basic education with some kindergarten

	Type of school		
	Community	General	Indigenous
1998	0.21	0.73	0.56
1999	0.15	0.74	0.59
2000	0.17	0.74	0.6
2001	0.19	0.76	0.59
2002	0.2	0.77	0.6
2003	0.3	0.81	0.63
2004	0.28	0.83	0.65
2005	0.3	0.85	0.69
2006	0.35	0.88	0.71
2007	0.36	0.88	0.72
2008	0.31	0.88	0.72

Source: School Census – México, 1998-2008

Age-grade distortion Previous chapters in this dissertation have discussed the issue of school delay, overage and their consequences. A substantial amount of literature shows that the most productive time to learn is relatively early in the life cycle and that school systems that have substantial portions of the student population with school delay may be impacting negatively on its students. Indeed, the literature on the long-term effects on education, achievement, fertility and even infant mortality rates underwritten by standardized entry policies speak to the importance of uniform school entry rules McCrary and Royer (2011); Dobkin and Ferreira (2010); Black et al.

(2008); Angrist and Pischke (2008). Age diversity can impact learning negatively in the classroom as age heterogeneity can present many pedagogical challenges to teachers.

Table 5.16 shows how compensatory and indigenous schools have more students beginning school at non-standard ages. While some progress in community and indigenous schools has occurred between 1998 and 2008, the gap between indigenous students and students in private and general public schools remains, symptomatic of systemic inequities.

Table 5.16: Percent of First graders by school type

	First graders six years and below		
	Compensatory	Indigenous	General
1998	0.54	0.74	0.9
1999	0.57	0.76	0.91
2000	0.47	0.78	0.91
2001	0.57	0.79	0.92
2002	0.59	0.79	0.92
2003	0.64	0.82	0.93
2004	0.69	0.84	0.93
2005	0.7	0.86	0.94
2006	0.61	0.85	0.94
2007	0.61	0.85	0.94
2008	0.72	0.86	0.94

Source: School Census – México, 1998-2008

Table 5.17 presents age distortion within classrooms, using ENIGH data on the indigenous population. Whereas approximately 29% of non-indigenous 1st graders are older than the rest of the students in class, 40% of indigenous students are older than their classmates.

As an equity policy in the public education system, indigenous schools have a bilingual curriculum. However, a recent and on-going qualitative and quantitative study of intercultural bilingual education in México reveals that the actual degree of bilingual education—even in indigenous schools—is low and varies widely from one school to another (Yonker Vales, 2004). Moreover, Ramirez (2006) argues that there are many practical obstacles to bilingual education in terms of textbooks, subjects and the 62 indigenous languages and many dialects present in México.

Table 5.17: Age-grade Distortion by Sub-groups

	Indigenous	Non-indigenous	All
1st grade	0.44	0.29	0.31
2nd grade	0.46	0.35	0.36
3rd grade	0.52	0.38	0.39
4th grade	0.5	0.38	0.39
5th grade	0.43	0.33	0.34
6th grade	0.46	0.33	0.34

Source: ENIGH-MCS 2010
Defined as percent of students who are more than one year behind
the age that is appropriate for their grade. Appropriate ages:
1st grade (6 years old); 2nd grade (7 years old); 3rd grade (8 years old), etc

In conclusion, the discussion so far shows that although equity of access to basic education in México on the basis of ethnicity may not be an acute concern, inequities prior to formal schooling, gaps in transition rates between grades and drop-out percentages continue to disproportionally burden indigenous populations. Issues related to age-heterogeneity and bilingual education serve to further compound these factors.

Outcomes

In the first six grades of formal education, national test scores indicate comparatively poor performance among children in indigenous and compensatory schools. Figure 5.2 illustrates some of these disparities among 6th graders in México. The data shows math tests scores by school type, as obtained from ENLACE. The observed disparities between community and indigenous schools, which serve moist of the indigenous population, and general schools remain over time and in other grades.

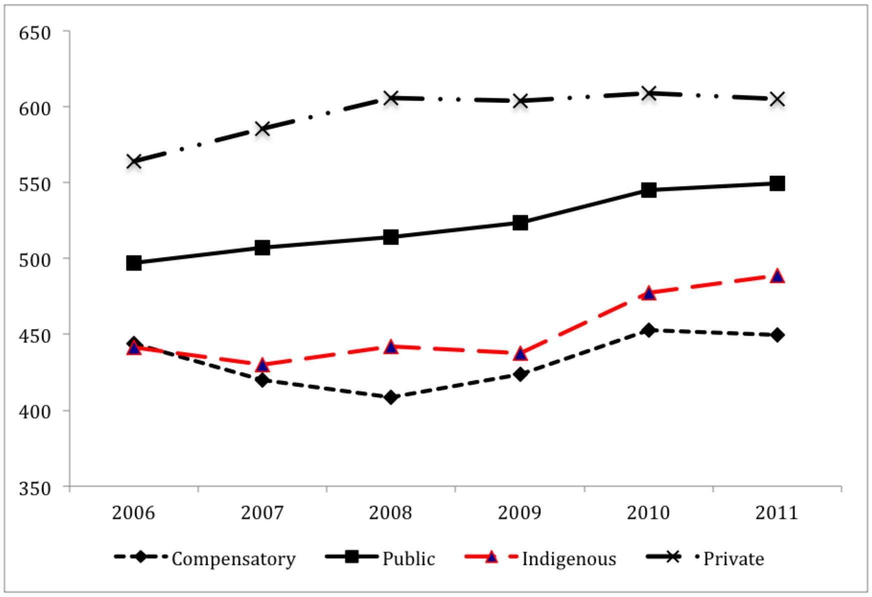

Figure 5.2: Sixth grade math scores by school type in the National achievement test (ENLACE)

Test scores have generally risen over time in México and this applies as well to indigenous students. Over a period of five school years, 3rd graders in indigenous schools improved by 0.57 s.d., with the greatest increase occurring among 3rd graders. By contrast, 3rd graders in compensatory schools increased only 0.19 s.d. Private and general public schools were in the middle, increasing by 0.37 s.d. and 0.47 s.d., respectively. In this way, the gap between indigenous schools and private and general public schools was reduced by 0.16 s.d. to 0.20 s.d. over five years. By the same token, 4th graders in indigenous schools improved by 0.49 s.d., comparable or greater to the 0.49 s.d. increase in private schools, and the 0.40 increase in general schools. A similar pattern occurs among 5th and 6th graders.

All in all, indigenous school math scores increased more than compensatory school math scores during this period. Nevertheless, as the data clearly shows, consistent disparities remain. As for Spanish achievement scores, indigenous and compensatory schools charted similar patterns, thus preserving pre-exiting patterns.

Lower secondary

An important national assessment is mandated for a sample of Mexican students at age 15. Students sit for the international standardized PISA exam covering math, science and reading. In this evaluation, the indigenous population of México amounts to only 2.6% of test-takers. Like other assessment measures, Table 5.18 illustrates the comparatively low achievement among indigenous students. In PISA 2009, the average math score for indigenous students was below the minimum achievement level (Level 1). In fact, the learning gap between indigenous and non-indigenous Mexican students was 0.8 s.d.—the same amount México scored below the average of all OECD countries. These test score gaps cross all academic skills. In particular, indigenous students at age 15 years are one full standard deviation behind the rest of the population in reading. Yet these indigenous students who sit for the PISA exam at age 15 are among the best: They have persevered through at least seven years of formal education while others have dropped out.

The wider gap in test scores at age 15 suggests that the inequality in learning outcomes on the basis of ethnicity increases after the end of basic education.

Table 5.18: México: Inequities in PISA achievement for the enrolled population

	Average Score		
	Math	Spanish	Science
Total	419	425	416
Girls	412	438	413
Boys	425	413	419
Wealthiest 50%	444	453	442
Poorest 50%	396	400	393
Spanish speakers	422	429	419
Indigenous	342	327	338

Source: PISA 2009

These learning inequalities cross all academic skills. In particular, indigenous students at age 15 years are one full standard deviation behind the rest of the population in reading. Yet these indigenous students who sit for the PISA exam at age 15 are among the best: They have persevered through at least seven years of formal education while others have dropped out. Better results might be expected on this basis alone, but De Hoyos et al. (2012) argue that the determinants of cognitive learning for indigenous high school students in México have a significant but regrettably negative correlation with math learning. This coefficient is a negative 0.5 s.d. for indigenous students while their non-indigenous peers have less negative—and even positive—coefficients.

5.5 The use of education in the labor markets: Returns to schooling investments

Differences in earnings are known to exist between indigenous and non-indigenous populations. As noted earlier, the existing empirical studies on the determinants of wages on the basis of ethnicity in México cannot identify indigenous individuals explicitly, so they have looked at income or earnings differences between indigenous and non-indigenous municipalities, where indigenous municipalities are defined as municipalities where 30 % or more of the population is indigenous. This is the criterion used in Table 5.19. This Table shows the mean monthly earnings by municipality. In 2000, individuals living in non-indigenous municipalities earned three times more than those living in indigenous municipalities. Following what appears to be the "recession pattern". In 2010, this gap fell to just greater than two times.

Table 5.19: Mean Earnings by Municipality

		2000				2010		
	Non-Indigenous		Indigenous		Non-Indigenous		Indigenous	
All	3601	1935	1136	3553	9163	7580	4119	8844
Male	3912	2201	1486	3853	9436	7894	4232	9115
Female	2952	1516	1080	2925	8912	7285	4019	8596

Source: ENIGH 2000 and 2010
Universe: all employed individuals. Earnings in last month

The 2010 data makes possible the identification of indigenous populations on the basis of language. This chapter makes use of the availability of these data to compute in more detail earnings gaps on the basis of ethnicity. On this basis, Table 5.19 shows average monthly income across age categories for indigenous and non-indigenous groups. In 2010, the indigenous population aged 20 to 29 earned more than the rest of the indigenous population, but still 41% less than non-indigenous earners of the same age. The Table also reveals another interesting fact: While non-indigenous earners actually earned less in 2010 than 2008, indigenous income remained almost constant—an indication that indigenous incomes were more resilient than their non-indigenous counterpart during the recent recession, an observation worthy of further research.

The present study uses the recent data identifying indigenous people to compute earnings differences on the basis of education. As expected, wage earnings are positively correlated with schooling. In 2008, non-indigenous university graduates earn four times more than non-indigenous workers without any education. By comparison, indigenous university graduates earn between four and five times their uneducated peers. Two years later, in 2010, non-indigenous university graduates earn between three and four times more than non-indigenous workers lacking similar education while indigenous university graduates earn five times their uneducated peers.

So while there are clear returns on educational investments for both indigenous and non-indigenous workers, the payoffs are not equal. At all levels of education, indigenous people earn less than non-indigenous. For example, in 2008, the wage gap for indigenous versus non-indigenous with a university degree was 39%; in 2010, this gap decreased to 19% (likely, though, because non-indigenous incomes fell rather than indigenous incomes rising). Even within the same sector, indigenous workers make less than their non-indigenous peers (though, again, the 8% 2008-2010 reduction in the difference probably reflects non-indigenous setbacks rather than indigenous gains).

A few studies have estimated the returns to schooling by ethnicity in México. Most have used data based upon indigenous municipalities (as determined by the 30% rule defined above) due to a lack of direct indigenous data (see Panagides 1994, Ramirez 2006). By contrast, Panagides (1994) estimated an earnings function using a household survey completed by individuals from two different indigenous areas (high versus low concentrations). In his analysis, Panagides attributed earnings differences to labor market discrimination as well as human capital differences. In 1989, the returns to schooling were lower for indigenous municipalities but they were close to each other for the two groups: high concentration municipalities had an 8.7% rate of return to a year of schooling while low concentration municipalities exhibited a 9.3% rate of return. However, updating the data, Ramirez (2006) found that the rates of return to education for these two populations had diverged even more over time. By 2002, returns to schooling in non-indigenous areas had increased but remained constant in indigenous areas. Like Panagides, Ramirez concluded that discrimination plays an important factor in these disparities.

Table 5.20 summarizes estimates obtained from Mincerian earnings functions carried out separately for indigenous and non-indigenous municipalities. During the last ten years, the rate of return to education among indigenous municipalities has increased 1% while it decreased by 3% for non-indigenous municipalities. For indigenous workers, the recent increase on returns may be somewhat surprising. Still, this increase is arguably consistent with human capital theory. Since the rate of return analysis does not include quality of schooling, the rising coefficients on education for indigenous municipalities may be reflecting the rewards to the greater quality of schooling

Table 5.20 summaries Mincerian earnings functions by indigenous municipalities. The estimated rates of return are higher than what might be expected—given the expansion of schooling in recent years, a source of potential dilution. During the last ten years, the rate of return on education among indigenous individuals has increased 1% while it decreased by 3% for indigenous individuals (perhaps because the average years of schooling among non-indigenous has, itself, increased by one full year). For indigenous workers, the recent increase on returns is somewhat surprising given the rapid expansion of schooling years for this population. Still, this increase is arguably consistent with human capital theory. Recall that indigenous schools improved the most over time, by more than 0.5 s.d. in test scores. If markets are supposed to reward improvements like this, then it makes sense that returns on education would reflect this dynamic—small but comforting evidence that human capital theory is applicable in the real world with real data. The fact that returns for non-indigenous municipalities decreased by 3% in the same period 2000-2010 must be left for another day of analysis.

Table 5.20: Returns to Schooling by Municipality

	2000			2010		
	Non-Indigenous (0% to 30%)	Indigenous (30% to 100%)	All	Non-Indigenous (0% to 30%)	Indigenous (30% to 100%)	All
Returns to Schooling	13%	14%	13%	10%	15%	10%
Ave. Years Schooling	8.3	4.6	8.2	9.3	7.4	9.2

Source: ENIGH 2000 and 2010

The analysis in this dissertation uses the Oaxaca-Blinder technique, which is used in labor economics to decompose earnings gaps between different groups in society and to estimate the role of discrimination in explaining those gaps. More specifically, the Oaxaca-Blinder decomposition is used to specify the relative role of different factors explaining the earnings gap between minority groups and the majority group in the country. In the present case, it is used to examine the determinants of the earnings gap between indigenous and non-indigenous populations. The method decomposes the gap into two parts: one part that represents variations in individual endowments of productive attributes or characteristics, and a second part that reflects the impact of differences in rates of return to those characteristics, which is often associated with the effects of discrimination. This decomposition assumes that in the absence of discrimination the estimated effects of individuals' endowments on the labor market are identical for each group. In addition, it assumes that discrimination is revealed by differences in the estimated coefficients of the earnings equations. Table 5.21 shows the coefficients of the Oaxaca-Blinder estimation.

But even with economic vagaries which sometimes impact non-indigenous populations worse than indigenous populations, and despite decades-long educational advances, indigenous peoples will continue to lag behind non-indigenous counterparts so long as their schooling is not equal and discrimination in the workplace may exist.

Table 5.21: Decomposition of Ethnic Earnings Differential, Indigenous Municipality

	2000		2010	
	Percent of the differential due to differences in			
	Endowments	Wage structure	Endowments	Wage structure
All pop	62.2	37.8	77	23
Men	65.6	34.4	71.3	28.7
Women	66.2	33.8	84.7	15.3

Source: ENIGH 2000 and 2010

5.6 Conclusions

> Me declaro a favor del pluralismo cultural, integrado por el concepto de una Patria grande y ligado por un sistema economico justo, a la vez que eficaz
>
> Sáenz (1939)

This chapter has documented the wide inequalities that exist between indigenous and non-indigenous populations in education, in poverty and in the labor market. Although some progress has been achieved in some indicators, huge inequities remain.

Consider poverty: the percentage of families in extreme poverty residing in municipalities where indigenous populations are concentrated dropped from 70.8% to 51.9% between 1992 and 2010, while the equivalent change for non-indigenous municipalities was from 18.7% to 16.9%. So, although progress has been made, the gap in poverty rates between indigenous and non-indigenous populations remains huge.

In terms of educational attainment, municipalities with the highest concentrations of indigenous populations increased their schooling levels by 2.9 years between 2000 and 2010. By contrast, non-indigenous communities increased their schooling only one year. But this narrowing of the schooling gap by 1.8 years did not eliminate the average schooling difference that still exists between these groups, which remains at approximately two years.

In terms of participation in Kindergarten, the percentage of students who are overage, and the average student achievement as measured by a variety of tests, indigenous children lag substantially below non-indigenous children. The analysis in this paper suggests that these differences in education quantity and quality partly explain the income and poverty gaps computed in this chapter. Rates of return to education estimated as part of this research are high for both indigenous and non-indigenous groups.

The inequities documented in this chapter require policy actions. From a humanist point of view, humans deserve a complete life which includes not only biological development—freedom from deprivation– but also psychological development—freedom to reason, choose and act (Kaushik and Lòpez-Calva, 2011). This is why Sen (1999) argues that governments should not seek to equalize resources. Governments should aim to equalize human capabilities. That is, what people are able to be and to do. In this way, schooling represents a social-wide investment in human capital. And while schooling entails a variety of opportunity costs in the form of forgone earnings and expenses (tuition, books, uniforms, etc.), the rates of return—including the indigenous population of México—indicates such investments are indeed worthwhile.

The goal, then, of México's education system should be to provide learners equal opportunities to fulfill themselves. There are four commonly used criteria to inform decision-making regarding resource mobilization and allocation: adequacy, equity, equality and efficiency (Benson 1995, Cohn and Geske 1990). Given the state of indigenous education in México, specific policies must be designed and implemented to increase bilingual education, school choice for indigenous students, and greater integration between indigenous and non-indigenous communities to reduce inequalities and accelerate economic development. There is no doubt that progress in these areas has been realized since the Mexican revolution, but the relative disparities between indigenous and non-indigenous communities remain stubbornly persistent.

Today, México needs to be an integrated country to reduce inequalities and boost economic development. Education is a necessary tool of this integration by supplying more equal initial conditions and by providing skill acquisition in a cultural diverse learning environment. Indigenous children, in particular, those in age to attend school, are not guilty of their poor learning performance. It is a failure of society and its educational system.

5.6.1 Tables and Figures

Table 5.22: E Population Distribution by State in México

percent of ethnic group in given state	Non-indigenous	Indigenous
Aguascalientes	0.99	0.01
Baja California	0.96	0.04
Baja California Sur	0.97	0.03
Campeche	0.76	0.24
Coahuila	1	0
Colima	0.99	0.01
Chiapas	0.68	0.32
Chihuahua	0.95	0.05
Distrito Federal	0.96	0.04
Durango	1	0
Guanajuato	1	0
Guerrero	0.77	0.23
Hidalgo	0.77	0.23
Jalisco	0.99	0.01
México	0.94	0.06
Michoacán	0.95	0.05
Morelos	0.96	0.04
Nayarit	0.94	0.06
Nuevo Leon	0.97	0.03
Oaxaca	0.57	0.43
Puebla	0.85	0.15
QuerÈtaro	0.98	0.02
Quintana Roo	0.65	0.35
San Luis Potosi	0.83	0.17
Sinaloa	0.98	0.02
Sonora	0.94	0.06
Tabasco	0.95	0.05
Tamaulipas	0.98	0.02
Tlaxcala	0.94	0.06
Veracruz	0.86	0.14
Yucatan	0.49	0.51
Zacatecas	0.99	0.01

Source: ENIGH-MCS 2010

Table 5.23: Male Educational Achievement by Municipios

	2000				2010			
	Non-Indigenous	Indigenous		All	Non-Indigenous	Indigenous		All
Population aged 15 and over		1	2			1	2	
Still in school (%)	11.3	8	7	11	13.2	12.9	10.7	13
If not still in school, highest educational achievement								
No Education	23.6	34.3	54.6	25.2	16.3	23.3	35.8	17.6
Incomplete Primary	5.7	8.6	10.8	6.1	4.4	4.6	8.2	4.6
Complete Primary	25.2	19.6	22.2	24.8	22.3	19.3	22.8	22.2
Complete Lower Secondary	24.8	22.5	7.2	24.1	28.7	28.6	21.6	28.3
Complete Upper Secondary	7.2	8	1.9	7	15.3	15.6	7.7	14.9
Complete University	12.6	6.5	3.3	12	11.6	7.7	3.6	11
Graduated school	0.9	0.5	0	0.9	1.5	0.9	0.3	1.4

Source:Author's calculation using ENIGH 2000 and 2010. Non-Indigenous refers to 0% to 30% of indigenous in the municipality, Indigenous 1 refers to 30% to 70% of indigenous in the municipality, Indigenous 2 refers to 70% to 100% of indigenous in the municipality

Table 5.24: Female Educational Achievement by Municipios

	2000				2010			
	Non-Indigenous	Indigenous		All	Non-Indigenous	Indigenous		All
Population aged 15 and over		1	2			1	2	
Still in school (%)	10.3	8.6	2.3	10	12.05	11.74	8.74	
If not still in school, highest educational achievement								
No Education	26.3	39	63.8	28.2	18.9	30.6	43.5	20.7
Incomplete Primary	6.6	6.6	8.8	6.6	4.7	6.3	7.1	4.9
Complete Primary	25.9	21.7	17.6	25.4	21.8	18.2	19.7	21.6
Complete Lower Secondary	25.8	23.7	6.5	25.1	27.3	22.1	18	26.6
Complete Upper Secondary	7.2	3.5	1.2	6.8	16.8	15.2	8.1	16.3
Complete University	8	5.5	2.2	7.7	9.7	7.1	3.6	9.2
Graduated school	0.3	0.1	0	0.2	0.9	0.6	0.1	0.8

Source:Author's calculation using ENIGH 2000 and 2010. Non-Indigenous refers to 0% to 30% of indigenous in the municipality, Indigenous 1 refers to 30% to 70% of indigenous in the municipality, Indigenous 2 refers to 70% to 100% of indigenous in the municipality

Table 5.25: Male Literacy by Municipality

	2000				2010			
	Non-Indigenous	Indigenous		All	Non-Indigenous	Indigenous		All
Age		1	2			1	2	
5 to 14	77.9	71.8	68.1	77.2	83.05	82.44	78.21	82.69
15 to 29	97	93.2	83.3	96.5	97.88	97.68	94.09	97.67
30 to 44	92.6	90.4	71.3	91.8	96.42	93.88	83.87	95.75
45 to 59	88.4	80.9	61.4	87.2	94.7	89.66	76.1	93.61
Older than 59	73.7	64	35.1	71.3	83.79	71.88	57.11	81.78

Source:Author's calculation using ENIGH 2000 and 2010. Non-Indigenous refers to 0% to 30% of indigenous in the municipality, Indigenous 1 refers to 30% to 70% of indigenous in the municipality, Indigenous 2 refers to 70% to 100% of indigenous in the municipality

Table 5.26: Female Literacy by Municipality

	2000				2010			
	Non-Indigenous	Indigenous		All	Non-Indigenous	Indigenous		All
Age		1	2			1	2	
5 to 14	79.8	80.8	71.9	79.6	83.85	80.12	80.04	83.42
15 to 29	94.9	94.7	78.6	94.5	98.81	95.2	92.91	98.33
30 to 44	92.5	81.6	56.2	90.8	95.9	87.92	75.69	94.59
45 to 59	84.5	62.1	51.8	82.4	91.36	76.58	55.58	89.12
Older than 59	66.4	42.7	26.4	63.4	77.02	52.17	27.68	73.41

Source:Author's calculation using ENIGH 2000 and 2010. Non-Indigenous refers to 0% to 30% of indigenous in the municipality, Indigenous 1 refers to 30% to 70% of indigenous in the municipality, Indigenous 2 refers to 70% to 100% of indigenous in the municipality

Table 5.27: Sample Demographics of Population by Municipios

	Non-Indigenous	Indigenous		All	Non-Indigenous	Indigenous		All
	(0% to 30%)	(30% to 70%)	(70% to 100%)		(0% to 30%)	(30% to 70%)	(70% to 100%)	
Male (%)	48.0	49.4	50.7	48.1	48.7	48.9	48.8	48.8
Average Age	27.2	26.1	27.4	27.1	29.9	28.6	27.6	29.7
Urban (%)	100.0	100.0	100.0	100.0	66.6	46.0	10.9	62.6
Married (%)–aged 15 and over only	50.6	52.2	57.5	50.9	43.8	46.2	44.5	44
Percent of Total Sample	91.4	5.3	3.4	100	90.1	4.3	5.6	100
Households	9099	596	394	10089	22232	2703	2720	27655
Sample Observations	37992	2595	1921	42508	85,241	10,219	12,321	107,781
Weigthed Population	90,036,953	5,203,960	3,321,237	98,562,150	101,594,973	4,891,777	6,252,949	112,739,699

Source:Author's calculation using ENIGH 2000 and 2010.

Table 5.28: Determinants of Poverty, Individuals

Independent Variable	Coefficient		Mean	Marginal Effect
Age	-0.01	***	37.76	0
Age Squared	0	***	1632.51	0
residents 0 to 15 years	0.16	***	1.81	0.06
residents 16 to 35 years	-0.04	***	2.1	-0.02
residents 36 to 65 years	-0.05	***	1.77	-0.02
residents 66 years and older	0.05	***	0.31	0.02
Incomplete Primary	-0.09	***	0.04	-0.04
Complete Primary	-0.32	***	0.21	-0.13
Complete Lower Secondary	-0.6	***	0.29	-0.23
Complete Upper Secondary	-1	***	0.19	-0.35
Complete University	-1.66	***	0.12	-0.46
Graduated school	-2.22	***	0.02	-0.5
Worker without salary	0.24	***	0.14	0.1
Worker salary	-0.03	***	0.67	-0.01
Agricultural owner	0.34	***	0.01	0.13
Agricultural worker without salary	0.69	***	0.06	0.25
Agricultural worker salary	0.54	***	0.08	0.2
Indigenous Household	0.32	***	0.1	0.12
Year	0.15	***	0.5	0.06
Constant	0.09	***		
State Dummies	Yes			
Mean of Dependent Variable	0.37			
Pseudo R-square	0.22			
N	186,644			

Logit regression; dependent variable takes on values of 0 and 1 (dummy variable) indicating whether person is poor
Source: ENIGH-MCS 2008 and 2010

Table 5.29: Determinants of Poverty, Households

	Coefficient		Mean	Marginal Effect
Age	0	***	43.23	0
Age Squared	0	***	2007.27	0
residents 0 to 15 years	0.18	***	1.8	0.07
residents 16 to 35 years	-0.06	***	1.81	-0.02
residents 36 to 65 years	-0.06	***	1.58	-0.02
residents 66 years and older	0.02	***	0.19	0.01
Incomplete Primary	-0.1	***	0.05	-0.04
Complete Primary	-0.31	***	0.22	-0.11
Complete Lower Secondary	-0.61	***	0.26	-0.21
Complete Upper Secondary	-1.06	***	0.16	-0.31
Complete University	-1.73	***	0.12	-0.4
Graduated school	-2.18	***	0.02	-0.37
Worker without salary	0.31	***	0.16	0.12
Worker salary	-0.03	***	0.62	-0.01
Agricultural owner	0.32	***	0.02	0.12
Agricultural worker without salary	0.71	***	0.09	0.27
Agricultural worker salary	0.49	***	0.08	0.19
Indigenous Household	0.29	***	0.1	0.11
Year	0.14	***	0.5	0.05
Constant	0.14	***		
State Dummies	Yes			
Mean of Dependent Variable	0.38			
Pseudo R-square	0.22			
N	109,452			

Logit regression; dependent variable takes on values of 0 and 1 (dummy variable) indicating whether person is poor
Source: ENIGH-MCS 2008 and 2010

Chapter 6

Conclusions

The Mexican people have made some important advancements in education. These are reflected in rising enrollment rates and growing educational attainment. But these successes remain tainted by wide gaps in access to education on the basis of income and ethnicity, and by substantial challenges in the quality o education provided by the school system.

This dissertation has presented empirical evidence and analysis of three key issues in the Mexican education system: 1) school accountability, which was examined by studying in detail the PAE program, a targeted intervention program pursued by the state of Colima in 2009 to identify and address the problems of low-performing schools, 2) age delay, which is a major phenomenon in the school system of México, and the effects of a national reform introduced in 2006-2007 that reduced the first grade entry age across all Mexican states, and 3) the educational disadvantages of indigenous peoples in México and their consequences, which are analyzed through the use of recent data allowing individual identification of this population.

Accountability Reforms and the PAE. In chapter 3, the dissertation conducted an evaluation of the Programa de Atención Específica para la Mejora del Logro Educativo (PAE), a targeted state-sponsored intervention program designed to provide low-performing schools with remedial resources in Colima, México. The research analyzed the effect of this compensatory program on the standardized test scores of 108 participating schools having the lowest learning outcomes in 2009, comparing them with a control group of non-participating schools.

By exploiting PAE's eligibility rules, a regression discontinuity method was used to estimate the impact on subsequent learning outcomes. Schools that participated in the program and a valid comparison group were followed for three years in order to compare their performance. The fact that the program was halted after only one year meant that the only realized interventions were those related to the program's preparation, which revolved around notifying schools as low-performing, identifying a school's main academic problems and devising a development plan to address those challenges. Thus, the program's effects in the short-run were confined to the impact of these informational and analytical activities, and –later—to any pedagogical programs implement by the schools on their own as a consequence of the information and analysis provided by PAE.

The results of this "natural experiment" confirm that the PAE program had a positive impact on average test scores in poorly performing Colima schools. Despite the fact that the program was ended after one year and therefore mostly provided information and a dissection of the educational problems faced by students in the PAE program, after only one year, test scores in PAE schools increased by 0.28 standard deviations vis-à-vis non-PAE schools and in fact, after three years, differences between the two groups of schools were no longer significant.

The results presented in this chapter indicate that full and wide dissemination of information detailing school quality is critically important for improving student achievement. When students, teachers and parents in a school know that their tests scores are low, and this triggers a process of self-evaluation and analysis, the process itself may lead to an improvement in learning outcomes. There may also be a motivational impact connected to the ranking of a school relative to others, linked to the "naming and shaming" social pressure that arises from being labeled a low-performing school. And, over time, these impacts can generate changes at the school level, with teachers reforming their pedagogy to improve the achievement of their lowest-performing students.

According to the results of the research in this chapter, it is not so much the inputs made available by an intervention program, but the signaling value of the program, the associated diagnosis and networking opportunities with other school officials and advisers which result in school improvements. Moreover, unlike the high-stakes consequences for schools in the United States, or the sacking of officials in England, or the lead with your feet school choice in the Netherlands, the policy (or at least de facto events) in Colima bore no punitive actions against school actors.

So while the PAE program in Colima was surprisingly and frustratingly short-lived, it's premature termination serves to highlight a largely unrecognized phenomenon: acknowledgment is, in some ways, virtually tantamount to improvement. After all, if you really understand the problem, effective solutions come much easier. If you don't understand the problem, no amount of "problem-solving" can be expected to work. This is why future research must focus on documenting how school administrators, teachers, parents and students interpret, internalize and react to indications that their school is underperforming.

Age Delay and the Effects of Reforms in School Entry Age: Is it Better to be the Head of the Mouse or the Tail of the Lion?. Chapter 4 of this dissertation explored the impact of school delay on student outcomes. The study employed two identification strategies. It used an exogenous variation in the age at which students enter school to examine the effect on ENLACE test scores. In addition, the research was able to incorporate into the analysis the presence of a reform in México which allowed younger children to enter school, a policy shift that exogenously changed the age composition of the classroom in the country

Prior to the 2006-2007 school year, the cut-off day for school entry in México had been September 1st. Since then, however, pupils aged 6 by as late as December 31 could start public school. Data related to this cut-off transition were reviewed and analyzed using a regression discontinuity method so as to estimate the causal effect of delayed school enrollment on math and Spanish test scores of students in third grade. A two-stage least square (TSLS) estimator was used wherein the source of identification is the variation in first grade entry ages which resulted solely from differences in dates of birth.

The results for various student cohorts and for various time periods indicate that older students scored higher than younger students. The reform impacted the discrepancy between those regulated by the new cut-off dates and those regulated by the old cut-off date(s) by 0.30 s.d. (comparing the 1998-1999 cohort which entered school before the reform with the 2002-2003 cohort, which entered afterwards).

The results also suggest age effects on education outcomes that are stronger for recent generations than for generations entering first grade prior to the reform. Underlying this result is the fact that there has been a large increase in test scores over time in México. The impact of age on schooling, specially the changes over time in the rate of return to age in terms of student achievement, may be connected to this trend. This requires further research as it involves analyzing the changes in resources and choices made by schools, teachers and parents over time, which may be impacting test scores (including pre-schooling and other reforms implemented by the government as well as the possibility of increased cheating or teaching to the test, among many other factors).

Because entry-age dates affect class composition, peer effects have changed for those schools affected by the 2006 change in the age of entry into school. Considering the impact of the average age of peers, students in the cohort 1998-1999 prior to the reform, who delayed school and attended a class composed, on average, of older students, scored lower by 0.08 standard deviations By contrast, the same effect after the 2006 reform was estimated to be greater, at 0.22 standard deviations

At a policy level, the research in this study suggests that schools or states with older students will tend to have higher tests scores. In the analysis, students enrolled in the same grade but one year older have test scores, on average, 8 points higher in ENLACE exams respect to lower average age classes. These results demonstrate that systematic de jure or de facto rules which influence classroom composition may lead to differences in average test scores. And schools that vary in average student age may have different measured student achievement just because of the age differences. Such an issue should considering when comparing the results of tests across schools or states for accountability purposes, if indeed there is age variation. For research purposes, it is an issue that should also be considered in assessing private-public differences in student achievement: private schools that have the discretion to choose older student –and exercise this discretion—may again have higher average test scores just because of this effect.

In conclusion, the impact of age on student achievement estimated in this dissertation is positive and significant (regardless the sample, the school year or birth cohort, the effect of school delay is half a standard deviation or above). This result, which is the outcome of the greater maturity as well as greater parental inputs obtained by being one year older when you enter school, suggests that it is indeed better to be the head of the mouse than the tail of the lion. However, it should also be emphasized that when a sizable portion of the student population delays enrollment, there are consequences on both students and the school system that are not measured by the impact of age on individual student outcomes examined in this dissertation. An examination of these impacts should be the task of future research.

At a policy level, while underage enrollment is no longer much of issue in México, overage children remains a big a problem. Part of the problem may be connected to redshirting but it is also related to socioeconomic status, and migration patterns (temporal and permanent). The fact that intra-cohort peer effects are positive for those who delayed enrollment—or close to zero for those in the same school year in public school—may suggest that children who postpone enrollment for more than one year (overage students) should transit with children of the same age, regardless of the grade and so called "catch-up" programs. While some non-systematic state programs exist to address overage children, overage is an issue that deserves closer public policy attention.

The Education Status of Indigenous Populations and their Socioeconomic Consequences. Chapter 5 presented the results of a detailed study of the educational outcomes of indigenous populations and the socioeconomic impact of schooling. The chapter utilized data from Encuesta Nacional Ingresos y Gastos de los Hogares, ENIGH) which, for the first time in 2008 and then 2010 identified indigenous populations.

The research in this chapter documented the wide gaps in socioeconomic status of indigenous and non-indigenous populations. For instance, although the percentage of families in extreme poverty residing in municipalities where indigenous populations are concentrated dropped between 1992 and 2010, , the gap in poverty rates between the municipalities where indigenous people concentrate and others remains huge, with extreme poverty in the former equal to 51.9% in 2010 and in the latter 16.9%.

The impact of increased education in reducing the poverty gap on the basis of ethnicity is substantial. Rates of return to education in México, estimated on the basis of Mincerian empirical earnings function carried out in this dissertation, tend to be high in México, ranging around 10%, including those applying to indigenous populations.

Unfortunately, despite some progress in reducing educational enrollment gaps, the study showed that the gaps in educational outcomes between indigenous and non-indigenous populations remain wide, whether in terms of overall educational attainment, participation in Kindergarten, the percentage of students who are overage, and the average student achievement as measured by a variety of tests. For instance, the results of the PISA tests for Mexican 15 year old students carried out in 2009 shows that the average math score for indigenous students was below the minimum achievement level (Level 1). In fact, the learning gap between indigenous and non-indigenous Mexican students was 0.8 standard deviations—the same amount México scored below the average of all OECD countries. These test score gaps occur across all the various tests in PISA, including math, reading and science. In particular, indigenous students at age 15 years are one full standard deviation behind the rest of the population in reading.

The inequities documented in this chapter require policy actions. Given that the language issue is a significant one for indigenous population, the reform of bilingual education programs –in terms of providing greater resources, more qualified personnel and improved pedagogical methods—may prove to be essential. Raising pre-schooling enrollment rates among indigenous populations is another area that should be emphasized, as any gaps at this level tend to generate a growing gap in student outcomes later in the school system. A focus of resources and policy attention on rural areas, where large portions of the indigenous populations live, needs to be considered. At all levels, whether because of delayed enrollment and overage, the poor conditions at home faced by students, the shortages of teachers and school personnel and other school inputs, etc., México's future educational policies need to re-focus their attention on the problems faced by its minority ethic groups.

Concluding remarks. Today, México must intensify efforts to reduce educational disadvantages and inequalities. Among some Mexican states, inequities in schooling may be having a rebound. This dissertation has provided research and empirical evidence in favor of a wide variety of policy measures, as stated in the earlier discussion in the present chapter. Overall, there is a clear need for greater coordination, information and support to local school actors by state and federal authorities.

The present study used theoretical and empirical analysis based in the field of economics of education to pragmatically evaluate the strengths and weaknesses of some aspects of the Mexican education system, including some key reforms. Though not claiming to be definitive, the data and subsequent analysis present a picture of education in México, one open to further discussion, reflection and, it is hoped, action.

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